SUPPLY, DEMAND AND DRILLING AND EXPLORATION ELASTICITIES IN NATURAL GAS: AN EMPIRICAL ESTIMATION FRAMEWORK

by

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The final copy of this dissertation has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline

Abstract

White, Kenton (Ph.D., Economics)

Supply, Demand and Drilling and Exploration Elasticities In Natural Gas: An Empirical Estimation Framework

Dissertation directed by Assistant Professor Jonathan E. Hughes

Chapters 1 and 2 estimate short-run supply and demand, and drilling and exploration elasticities in U.S. natural gas. The modeling framework presented here is the first to utilize weather-related instruments to identify both demand and supply-side parameters in natural gas. Weather shocks in the current month shift demand, permitting identification of short-run supply and drilling and exploration curves. Lagged, weather-induced storage shocks shift supply, permitting identification of the short-run demand curve.

Preferred estimates of aggregate demand range from (-0.14) to (-0.19). Elasticity varies by consumer type with industrial users the most inelastic at (-0.20) and residential utilities the most relatively elastic at (-0.46). Electricity generators exhibit elasticity of (-0.21). Estimates of supply elasticity range from (0.98) to (1.28). OLS regressions show that uninstrumented estimates are significantly downward biased.

Estimates of drilling and exploration activity first show a statistically significant increase five to six months after a price shock. This is the first study to examine the price response dynamics of drilling activity on a time scale shorter than one year. Maximum elasticity for the exploratory wells is (1.0), for developmental wells is (1.24), and for the number of active rotary rigs is (0.57). Again, OLS regressions reveal that uninstrumented estimates are significantly downward biased.

Chapter 3 examines the effect of entry on incumbent airline price dispersion. Three econometric methods are employed; a long-range event study, a control function and 2SLS regression. The primary hypothesis tested, is that dominant capacity share at the origin airport provides proportionately more protection for an incumbent's premium fares. There is some evidence that this occurs. Airlines with greater than 50% or 75% share are found to decrease base fares more than premium fares in response to competitor entry, although the effects are not statistically significant.

The 2SLS regression finds that entry on a route by a low cost airline decreases incumbent price dispersion 26% and average fare by 68%. Entry by a legacy airline decreases incumbent price dispersion by 18% and average fare by 10%. Additionally, similar to other recent works incumbents are found to consistently decrease fares several quarters before entry actually occurs.

To Jen, the ***other*** *kind of doctor, whose love and companionship means everything.*

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"I like to cook my family and pets. Use commas, save lives."

Which clearly illustrates why, in the pursuit of clarity, the role of good punctuation cannot be overemphasized.

Also, I thank Patricia Holcomb, the graduate program coordinator. Her tireless (but hopefully not tiresome) efforts to ensure that, on my wandering, occasionally digressive journey from PhD candidacy to dissertation defense, I did not overlook the necessary paperwork or deadlines, is greatly appreciated.

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Finally, I would especially like to thank my wife, Jen, to whom this work is dedicated. I cannot imagine anyone with whom I would have rather shared the joys and difficulties of this stage of our lives. She listened with gracious attention every time I needed to express my enthusiasm for some epiphany, positive development, or new idea, no matter how obscure or technical. And as a consequence, I am proud to note, she is now confidently using terms in the economist's vernacular like, *supply and demand, elasticity*, and "*skedasticity*".

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Chapter 1

SHORT-RUN SUPPLY AND DEMAND ELASTICITIES OF NATURAL GAS

Introduction

The historically low price of natural gas in the last decade[1] has had many causes. The improvement of horizontal drilling and hydraulic fracturing technology has led to abundant domestic supply with the discovery of large shale gas reservoirs in the West, Midwest and Northeast United States. The lack of LNG export infrastructure and federal bans[2] have prevented exports. The completion of a 20-year deregulation campaign by the federal government has helped to make the industry more dynamic and competitive than ever before. Additionally, the gradual pace at which electricity generators and industrial users have adopted natural gas in previous decades has held growth in domestic demand low relative to production increases.

[1] With the exception of price spikes following September 11, 2001, winter of 2005/2006 and the beginning of the financial crisis in 2008

[2] Bans have been lifted on select export projects beginning in May 2013

More recently, however, the adoption of gas in industrial and electricity generation sectors has begun to accelerate as users perceive that market conditions are likely to sustain low natural gas prices well into the future. Adoption has benefited firms in these industries as well as the U.S. economy as a whole.[3] In the summer of 2012 the percentage of electricity generated by natural gas exceeded that generated by coal for the first time in U.S. history.[4] Natural gas has been widely credited with helping to reduce U.S. CO_2 emissions.[5,6] While the public debate spins around the potential ills of fracking, the industry continues to undergo structural changes as it adjusts to the windfall of domestic shale gas. Gas markets are poised to experience a number of fundamental shifts in supply and demand and it will be especially valuable for market participants and policy makers to accurately forecast the impacts on base prices. An improved understanding of contemporary gas market dynamics and parameters will be necessary to make reliable price forecasts. In particular, an economic model which identifies the causal effect of price on supply and demand could improve the industry's notoriously poor price prediction models.

An additional contribution of this paper is that it replicates an estimation method recently developed for agricultural markets. Roberts and Schlenker (2013)

[3] A recent economic impact study found that natural gas contributed more than $380 billion to the U.S. economy
[4] From the EIA
[5] From the EPA; A kilowatt hour of electricity from natural gas has only about one third of the direct CO2 emissions as a kilowatt hour generated from coal or about 40% of the CO2 emissions from coal once methane leaks are taken into account.
[6] From the Yale Forum on Climate Change and the Media; The transition away from coal to gas electricity generation is estimated to have reduced U.S. carbon emissions by 100 million metric tons since 2005. It is credited as the single largest contributing factor to the nearly 12% decline in U.S. CO2 emissions that occurred from 2008 to 2013.

apply a similar methodology to estimating elasticities of corn, wheat, soy and rice. In some ways, it is natural to adjust their estimation framework to natural gas because of the similarities to agricultural markets. Both markets rely heavily on storage, are affected by weather, and influenced by expected price. The application of this estimation framework across different types of markets demonstrates its robustness for estimating elasticities. It implies that this method may be applicable in other storage-dependent commodity markets; especially, where either demand or supply is influenced by weather (e.g. oil, natural gas liquids, cocoa, and coffee).

Review of the Literature

This paper's estimation method deviates from standard practices in a long literature estimating natural gas elasticities beginning with Balestra and Nerlove (1966). In the literature, demand and supply are generally estimated alone rather than together. Demand and supply are often estimated with the assumption that price is exogenous or by using autoregressive time series models. Most studies do not account for the endogeneity of price. In fact, many demand estimation models explicitly assume that price is exogenous [Elkhafif (1992); Jack Wilkinson (1983); Beierlein, Dunn & McConnon (1981); Danielson (1978); Berndt & Watkins (1977)]. Others assume supply is perfectly elastic or that wellhead price regulation makes simultaneous equation estimation impossible or inappropriate [Balestra and Nerlove (1966); Blattenberger, Taylor and Rennhack (1983); Gowdy (1983)]. Where simultaneous equations of demand and supply have been estimated they have tended to find negative supply elasticity [Krichene (2002); Chermak and Patrick

(1995)]. Still others have estimated supply and demand with cointegration and error correction models [Krichene (2002); Doane & Spulber (1994); Beierlin, Dunn & McConnor (1981)].

A few attempts to estimate demand with instrumental variables have been made. Barnes, Gillingham and Hagemann (1982) estimate residential demand using price shocks of substitute fuels as instrumentals for natural gas price in a single equation model. They estimate residential demand of individual households rather than for local distribution companies (LDCs) and utilities, however, making their estimates incomparable with this paper. There are two efforts to estimate demand with two-stage and three-stage least squares [Bowdy (1983); Krichene (2002)] which are most similar to this paper. Bowdy (1983) finds local demand elasticities that range from -0.12 to -1.49 for industrial gas users in New York. Krichene (2002) finds aggregate U.S. demand between -0.01 and -0.39; although, the estimates have large standard errors and are not statistically significant. In both studies the price of alternate fuels are the instruments used to identify demand. Unfortunately, these variables are weak instruments for gas price. Additionally, there is concern that alternate fuel prices could be correlated with demand and therefore not appropriate instruments. This study improves on previous simultaneous equation estimations by using, exogenous, weather-related instruments that are strongly correlated with price. The weather-related IVs used in this paper generate a tighter range of elasticity estimates across model specifications and are statistically significant.

Aside from issues of price endogeneity and weak instrument problems, significant changes in the natural gas industry in recent years warrant a re-estimation of price elasticities. Most academic work on this subject was undertaken prior to the year 2000.[7] The completion of federal deregulation in 2000 and vast improvements in drilling technology have drastically altered the industry. In order to construct an improved estimation framework it is necessary to understand how institutions in the industry have responded to regulation changes and the abundance of domestic shale gas.

Weather, Storage and Price

Thousands of producers, millions of consumers and well-developed spot and futures markets have transformed segments of the U.S. natural gas industry into commodity markets characterized by intense competition. As in any market, it is empirically difficult to separate supply and demand in the market equilibrium of prices and quantities because they are simultaneously determined.

Weather is a natural instrument for supply (Mayer 1977; Mu 2007). Severe cold weather in winter increases demand; this permits identification of the supply curve. Similarly, abnormally hot weather in the summer increases the demand for space cooling and natural gas electricity generation. As long as weather-induced shifts in demand are unrelated to unobserved shifts in production capacity, then weather shocks can be used to make causal inferences about the effect of price on

[7] In fact all but a handful of academic studies on natural gas supply and demand elasticity were performed prior to 1990

short-run supply decisions. Given the well-established effect of weather on demand, it is somewhat surprising that weather-based instruments have so rarely been used to identify short-run supply in natural gas.

The estimation framework proposed here relies on exogenous weather shocks to identify short-run demand as well as supply. The effect of storage on demand has been widely examined in the competitive storage literature [Scheinkman and Schechtman (1983); Bobenrieth H. et al (2002)]. In this paper, consecutive, compounding weather shocks are assumed to cause changes in storage levels; changes in storage levels constitute shifts in supply, which can be used to identify short-run demand.

Intuition for the identification strategy is demonstrated in the following example. Imagine the U.S. experiences an unusually mild winter and the demand for natural gas is lower than anticipated; demand shifts in and price falls. In response to lower prices producers allocate additional quantities to storage in the current month. The sensitivity, with respect to price, of producer decisions to reinsert gas into storage or alternatively, to sell into market, is the short-run supply elasticity. Short-run supply elasticity can be identified by instrumenting for spot price with current month weather shocks in the supply equation.

Additionally, the increase in storage levels shifts out future supply. If storage increases occur in consecutive months, due to compounding weather shocks, the shift in supply will be significant enough to move price and identify demand.

Demand elasticity can, therefore, be identified by instrumenting for spot price with the sum of weather-induced storage shocks in previous months.

In the simultaneous equation framework current weather shocks are used to identify supply elasticity if they are included in the demand equation and excluded from the supply equation. Likewise, weather-induced storage shocks in previous months are used to identify demand elasticity when they are included in supply and excluded from the demand equation. The main assumption necessary for demand identification is that, after controlling for current month weather shocks, the sum of weather-induced storage shocks in previous months affects demand only through its effect on price. The main assumption necessary for supply identification, is that current weather shocks do not affect production capacity. The defense of these assumptions is the objective of the next section.

Methodological Concerns

Weather-induced Storage Shocks and the Exclusion Restriction

In order for weather-induced storage shocks to satisfy the exclusion restriction as instruments for price in the demand equation, they must not be correlated with current consumption through any mechanism other than their effect on spot price. This could be problematic if, consecutive months of compounding weather shocks are correlated with weather shocks in the month that follow. This would be the case if consecutive months of storage depleting weather shocks tend to be followed by a month in which weather shocks drive abnormally low demand. In this instance, the magnitude of the demand elasticity would be overestimated; the higher price driven by storage depletion shocks would appear to explain decreased demand that is actually due to both the price increase and the low demand weather shock. Fortunately, it does not seem likely that compounding weather shocks of one type should systematically be followed by a weather shock of the opposite type.

Admittedly, it is more likely that compounding weather shocks would be systematically followed by a month with a weather shock of the same type. As would be the case if consecutive months of storage depleting shocks are followed by a month of weather shocks that drives abnormally high demand. Here the magnitude of the demand elasticity would be underestimated since strong weather-driven demand, following months of storage depletion and high prices, would seem to indicate extreme insensitivity to price. In this paper, I assume that the extent of correlation between compounding weather shocks and the weather in the following month in the sample is not atypical. If months of compounding weather shocks are correlated with severe weather in subsequent months in the sample in a way that is unusual, then my estimates may be biased in one of the ways described above.

The Problem of Short-Run Endogenous Production Response

It is necessary to address the notoriously common perception in the literature and elsewhere that the production rate of natural gas responds immediately to price. This paper argues that both short-run demand and supply elasticities can be derived from exogenous weather-based instruments. There is little doubt that weather promptly shifts demand for natural gas. It would, therefore, be a particular nuisance to this paper's identification strategy if production is also endogenous to price. This section examines the issue in detail and demonstrates that any short-run, causal links going from price to production are minimal or non-existent.

Production would be endogenous to price in the short run if, for example, the rate at which gas is extracted from reservoirs changes more or less instantaneously with price. It is generally understood that drilling new wells to increase production capacity takes time and effort. Producers must secure leases, mineral rights and drilling permits in addition to building roads, pipelines, and mobilizing drilling rigs and personnel. Increasing capacity immediately by drilling wells is not possible. The concern, with respect to endogenous production, originates from the perception that gas wells can be easily shut in and flow rates reduced when prices are low. It would be difficult to estimate short-run supply elasticity if flow rates from existing wells are adjusted instantaneously with weather shocks. It should be reiterated that it is assumed producers *can* respond to weather shocks, but only by allocating more or less of their production to storage. This is what allows the identification of short-run supply. Fortunately for econometricians, if not well owners, a number of institutional and technological constraints prevent systematic, industry-wide, production rate responses in the short-run.

First, a significant portion of natural gas is associated gas, meaning that it is contained in a reservoir along with crude oil. Gas may sit on top of the oil in a gas cap, it may be dispersed within the reservoir along with oil, or it may be dissolved in the oil itself. The conditions of associated gas along with geologic features of the well determine whether or not it can be produced separately from oil. Where possible, producers use reservoir management techniques to control the extraction rate of oil and gas separately. Generally, extraction rates of both oil and gas are set to favor the recovery of oil, since it is more profitable.

Second, in the last decade, a growing proportion of natural gas production has come from low permeability sandstones, shales and coal bed methane. Production capacity of "tight gas" has increased dramatically due to improvements in horizontal drilling and fracking technology. Fracked wells produce at higher rates, but are more expensive. There is considerable uncertainty regarding the ability to return "tight gas" wells to prior production levels after being reduced or shut in. For this reason, operating companies generally do not tamper with tight gas wells' production rates.

Third, the majority of gas wells, including conventional ones, are bound by layers of contractual constraints; these include leasing and royalty agreements with land and mineral rights owners, as well as federal and state regulations. These constraints can stipulate that producers sustain production at rates which optimize the estimated economic value of a reservoir. A decision by well operators to shut in or temporarily reduce flow rates could decrease the total amount of recoverable gas. Even in cases without contractual constraints, producers must balance a decision to shut in wells against potential lost reserves and the cost to reopen wells later. Counter to common perceptions, the decision to shut in a well is neither cheap nor easy and is infrequently exercised.

The industry's reticence to shut in wells is readily observed. A series of figures is included in the *Tables and Figures* section to illustrate this fact. Figures 1 and 2 reveal no discernible correlation between monthly production and U.S. population-weighted HDD and CDD. Seasonal variation in HDD and CDD is generally predictable; this indicates that firms do not predetermine production capacity to match seasonal demand. Figures 3 and 4 show production by deviations of HDD and CDD from climate normals; there is no correlation between weather shocks and production. This demonstrates that firms do not adjust production rates in response to weather shocks.

Finally, figures 5 and 6 plot production on weather-related price changes. Weather-induced price movements are the fitted values from a regression of price on current month weather shocks. Figure 5 plots these predicted values of price on production; there is no visible correlation. Figure 6 examines whether there is a delayed production capacity response. It plots predicted values of price, from a regression on the sum of four months weather shocks, on production; again there is no clear correlation. Taken together, figures 1 through 6 offer strong evidence that producers' short-run production rate is fixed; total industry production does not adjust to seasonal demand levels, demand spikes, or exogenous movements in price.

It is clear that institutional and technological constraints make any quick, industry-wide production capacity adjustments impossible or undesirable. The obstacles facing producers who could wish to respond quickly to demand shifts effectively mitigate concerns of an endogenous production capacity response in the short-run. Consequently, the main decision faced by producers in the short run is how much gas to sell down pipeline at current prices and how much to reinsert into storage.

Given time, of course, producers have the ability to change production capacity. Long-run production capacity is determined primarily by producer decisions about when and whether to drill new wells. The rate at which producers explore and drill new wells to replace naturally declining production capacity has significant implications for production rates six months to several years in the future. Modeling long-run supply is therefore more complex. It cannot be identified using weather shocks from a single month as an instrument for price. For this reason, parameter estimates from this model should be used with caution when forecasting anything beyond short-run supply and demand response.

Furthermore, it is likely that weather-induced storage shocks *can* eventually shift production capacity. Producers are able to complete and operate new wells within five to six months of a storage shock (See Chapter 2). Weather-induced storage shocks will therefore, not satisfy the exclusion restriction necessary for estimating demand elasticity beyond the short run. Long-run elasticities of supply and demand are a component of natural gas markets that requires additional study and further adjustments to the current method, or a new estimation framework altogether.

A Formal Model of Supply and Demand

A formal model utilizing random weather and weather-induced storage shocks to identify short-run supply and demand elasticities is now developed. The theory of competitive storage is at the foundation of this framework. Storage by both producers and end-users is an important feature of natural gas markets. Natural gas is characterized by relatively smooth production and sharp, seasonal consumption patterns. Storage of gas produced in off-peak months allows suppliers to meet high and volatile demand during winter and summer. This makes gas prices less variable and more autocorrelated than they would be without storage capabilities. In the market equilibrium, it is not necessary to set price so that the quantity demanded in the current month equals the current month's supply. Instead, the quantity delivered to end-users z_t equals production q_t plus the net withdrawals from storage x_t (withdrawals minus insertion of both producers and end users).

$$z_t = q_t + x_t \qquad (1)$$

Some of the quantity delivered, z_t, is contractually arranged in periods preceding month t. End-users actual consumption c_t cannot be entirely anticipated, however, and is equal to the quantity contracted subject to a multiplicative i.i.d. random weather shock w_t.

$$c_t = w_t * \lambda_{t-i} \qquad (2)$$

The portion of contractually arranged delivery is λ_{t-i} with the delivery quantity agreed to via a forward contract in month t-i. Residual or excess demand that is greater than contractually prearranged quantities must be met with purchases in the spot market. Residual demand in the current month is r_t. Alternatively, consumption can then be defined as,

$$c_t = \lambda_{t-i} + r_t \qquad (3)$$

When r_t is positive it represents the need for additional purchases from the spot market by end-users because consumption is greater than contracted delivery amounts. When the residual demand r_t is negative it indicates that contractually arranged quantities exceed actual consumption in the current month. In this case all gas that is delivered but not consumed must be restored by end-users.[8] Substituting (1) into (2) and then equating this with (3) demonstrates that residual demand, r_t, is a function of exogenous weather shocks w_t; this is shown in equation (4).

$$\lambda_{t-i} * (w_t - 1) = r_t \qquad (4)$$

Furthermore, short-run production, q_t, is fixed and contracted quantity, λ_{t-i}, is predetermined, therefore, an increase in residual demand, r_t, can only be achieved by a symmetrical and opposite movement in net withdrawals from storage x_t. Equation (5) states that consumption cannot exceed total quantity delivered. Equation (6) is equivalent; it simply restates (5) in terms of forward commitments,

[8] Or a storage company must be paid to store the gas for them.

residual demand, current production and net withdrawals from storage. This equation shows that r_t and x_t have an exact, reciprocal relationship in month t.

$$c_t = z_t \tag{5}$$

$$\lambda_{t-i} + r_t = q_t + x_t \tag{6}$$

Atypical or unforeseen purchases made in the spot market will cause greater than anticipated storage level depletion. It can then be extrapolated, that a weather-driven decision by end-users to purchase additional gas requires a reciprocal action by producers; they must withdraw from storage to meet increased demand. The consequence, is that producer storage levels, x_t, are influenced by the same exogenous weather shocks, w_t, that influence residual demand r_t. In this paper's identification strategy it is assumed that several months of compounding weather shocks are required for the effect on storage levels to be sufficiently large to move price and identify demand.

Utilization of Competitive Storage Theory

A number of studies on competitive storage examine the effect of demand for inventories on commodity price. While the nuances of this literature are expansive, I exploit just two main ideas. The first, explicitly detailed above in the *Formal Model of Supply and Demand,* is that storage allows consumption to be transferred through time. The second, is derived in Scheinkman and Schechtman (1983), wherein the authors demonstrate that in rational, competitive storage model equilibrium, exogenous shocks are optimally divided between current consumption and inventory adjustments.

From these foundations the model diverges from the types of models most often depicted in the competitive storage literature. In this model, profit maximizing producers and utility maximizing end-users make two, sequential decisions. The first decision, made by end users, is the quantity of gas, λ_t, they commit in the current month, to receive and pay for in future months. Abstractly, the function $g(\lambda_t)$ can be interpreted as the perceived price risk of forward contracts from the point of view of end-users. Normally, risk of forward contracts is a function of both quantity commitments and contract duration. Due to low volume risk and increased price volatility in the last decade, however, forward contracts that stipulate larger quantities or longer contract durations have been perceived to confer greater price risk on end-users. Since this paper estimates short-run elasticities, increases in $g(\lambda_t)$ are here restricted to represent increases in the quantity of gas only (and not the contract duration). In other words, it increases perceived risk for end-users to commit to marginally larger quantities of gas at a future date. The cost of binding forward contracts $g(\lambda_t)$ is, therefore, assumed to be increasing and convex in quantity.

The second decision, made by producers, is how much gas to sell in the spot market to meet residual demand r_t. A fraction of gas reinserted into storage, $-x_t$, is lost and short-run supply decisions to increase storage must be balanced with consideration to convex storage cost $\theta(-x_t)$, as well as estimated future revenue from an expected increase in price $E[p_{t+i}]*(-x_t)$. Gas sold down pipeline to end-users, $w_t * \lambda_{t-i}$, is consumed; this gives consumers utility $u(w_t * z_t)$ and generates revenue $p_t * (q_t + x_t)$ for producers.

The Bellman equation for the social maximization problem is therefore

$$v(z_t) = \max_{x(t)\lambda(t)}\{u[\lambda_t * w_{t+1}] - g(\lambda_t) + p_t * (q_t + x_t) - \phi(-x_t) + \delta E[p_{t+1}](-x_t) + \delta\, E[v(z_{t+1} * w_{t+1})]\}$$

subject to

$$z_{t+1} = (\lambda_t + r_{t+1})$$
$$z_t \geq 0 \qquad \lambda_t \geq 0$$

Profit maximizing producers achieve the socially efficient outcome in the social planner's problem by optimally balancing the marginal cost of storage and the expected change in prices. Utility maximizing end users optimally balance the perceived risk of forward purchase commitments given expected future consumption and expected price. As always, the marginal utility of consumption in the social planner's problem is given by spot price. When price is low producers benefit by reinserting gas into storage and waiting for market conditions to improve. As a result, storage levels increase shifting out future supply and lower consumers' expected price for the coming months. The reverse occurs when price is high. In either case, producers continue to adjust storage levels until discounted future price equals the current price. The decisions made by end-users are similar since they must choose whether to increase commitments and accept greater price risk or satisfy increased residual demand with additional purchases in the spot market at future prices and incur volume risk.

The key theoretical underpinning of this formalized model is that weather shocks affect both current consumption and future supply. Current period weather shocks shift demand and result in movements along the supply curve. Weather-induced storage shocks shift future supply and result in a movement along the demand curve. Essentially, it is established that weather creates exogenous instruments for both price and expected price. These instruments can then be used to identify supply and demand in a 3SLS simultaneous equation estimation.

Instruments and the Identification Strategy

There is substantial descriptive evidence that weather and weather-induced storage shocks affect price. The fact that weather drives gas demand is well known and accepted. Figures 7 and 8 in the *Tables and Figures* section demonstrate the weather sensitive nature of demand. Figure 7 shows a strong, positive relationship between HDD and market-wide gas consumption. Figure 8 reveals a strong, positive correlation between CDD and gas consumption by electricity generators. This reflects the high demand for electricity during months with peak air conditioning use. The effects of CDD on market-wide gas consumption are more muted.

Figure 9 shows the effect of weather-shocks on storage levels. In months where HDD or CDD were above average (and demand was higher) storage levels are below average. Although the correlation is not immediately apparent, in regression there is a statistically significant and negative relationship between storage and weather shocks in the previous month.

Figure 10 displays the cumulative impact of weather shocks on storage. The sum of three months storage shocks are plotted on the sum of four months weather shocks; the sum of weather shocks from the three concurrent months and one preceding one. The relationship is visually and statistically stronger.

Figure 11 shows the generally negative relationship between detrended, natural log of Henry Hub spot price and the sum of three month weather shocks. The detrended measure of log price is constructed by regressing it on a polynomial time trend and using only the residuals.

Also, an extended number of cases in which demand elasticity is estimated with NYMEX futures prices are estimated and included in the *Tables and Figures* section. This is to account for the fact that end users may make forward contract commitments based partially on futures prices, or expected price. Figures 12 through 15 plot detrended, natural log of NYMEX futures prices on the sum of weather shocks. The measures of price in each figure are the 1, 2, 3 and 4 month NYMEX futures price respectively. Similar to spot price, the sum of three month, weather-induced storage shocks are negatively correlated with futures prices.

Descriptive evidence is widely consistent with the claim that weather shocks and weather-induced storage shocks generate significant, exogenous variation in natural gas spot and futures prices.

Empirical Model

The empirical supply and demand equations are the following

$$\text{Supply: } ln(z_t) = \alpha_s + \beta_s\, ln(p_t) + \delta \textstyle\sum_{i=1}^{3} stor_{t-i} + \Delta_d x_t + f(t) + u_t \quad (1)$$

$$\text{Demand: } ln(q_t + x_t) = \alpha_d + \beta_d\, ln(p_t) + \gamma w_t + \Delta_s x_t + g(t) + v_t \quad (2)$$

The quantity of natural gas delivered in a given month is z_t and is exactly equal to the sum of production and the net withdrawals from storage $q_t + x_t$. The price p_t is the Henry Hub spot price. In a series of extended cases the model is estimated with NYMEX futures prices in the demand equation. These are not the preferred specifications but results are included in the *Tables and Figures* section for comparison. The elasticities of supply and demand are β_s and β_d respectively. w_t is the random weather shock which shifts consumption in the current period. $stor_{t-i}$ is the lagged weather-induced storage shock which shifts supply. The sum of three previous storage shocks is used in order to capture sufficiently large shifts in the supply curve. The determination over how many months to sum weather-induced storage shocks for the IV was made by comparing the first stage regressions using the sum of two, three, four, five and six previous months. The first-stage regressions revealed that the sum of three preceding months' storage shocks is the strongest predictor of price; it therefore results in the most precise elasticity estimates in stage two.

x_t are additional controls including the price of oil, net gas imports and a variable for the length and severity of hurricane supply disruptions; hurricane disruptions are included only on the supply side. *f(t)* and *g(t)* are year fixed effects or polynomial time trends included to control for technological change, population growth and general macroeconomic conditions. u_t and v_t are the error terms and include all unobserved factors that shift supply and demand.

Henry Hub spot price (or NYMEX futures prices in the extended cases) is the key endogenous variables on the RHS of supply and demand equations. One clear way in which this identification strategy represents an improvement over previous estimation methods is that it enables weather-related instruments to be used for price in both the supply and the demand equation. By contrast, as previously stated, most studies assume price is exogenous. Weather is an ideal instrument since it is unlikely to be correlated with unobserved shifts in production capacity or other, non-weather related demand shifts that affect equilibrium prices. When the endogeneity of price is not addressed, elasticity estimates of supply and demand would most likely be closer to zero. This occurs because an unobserved, positive shift in supply decreases price; this creates a negative correlation between the supply error term and price. Similarly, an unobserved, positive shift in demand increases price; this creates a positive correlation between the demand error term and price. Both circumstances make demand and supply appear less responsive to price. Alternatively, if unobserved supply and demand shifters in the error terms, u_t and v_t, are correlated with each other, then biases could go either way. OLS estimates in this paper and most previous studies do, however, report elasticities closer to zero.

Additionally, one variation of the model specifications uses gross storage shocks as an instrument instead of weather-induced storage shocks. The benefit of gross storage shocks is that they are a stronger predictor of price and generate demand estimates with smaller standard errors. Since much of the total variation in storage levels is due to factors other than weather, however, this instrument is less credibly exogenous. In order to minimize the potential for correlation between gross storage shocks and demand, gross storage shocks are detrended with a quartic polynomial time trend. The detrended variable is less likely to be correlated with general macroeconomic conditions that could also be correlated with demand.

First Stage Regressions

In the supply equation, Henry Hub spot price is used as the measure of the U.S. market spot price, p_t. This is appropriate because Henry Hub is the most important natural gas distribution center in North America. Prices reported at Henry Hub are generally used as the base price for all other trading centers. All movements in other local market prices used by producers are closely correlated with movements in Henry Hub spot prices.

The first-stage of supply regresses natural log of Henry Hub spot price on HDD and CDD shocks, lagged weather-induced storage shocks, and a polynomial time trend of order I and the control variables. Current month weather shocks are the instruments for spot price that identify short-run supply and are excluded in stage two. The first stage supply regression is:

$$ln(p_t) = \pi_{s0} + \gamma w_t + \Delta x_t + \delta \sum_{i=1}^{3} stor_{t-i} + \sum_{i=1}^{I} \rho_{si}\, t^i + \varepsilon_{st}$$

The first-stage for demand again, regresses natural log of Henry Hub spot price on HDD and CDD shocks, lagged weather-induced storage shocks, control variables, and a polynomial time trend of order *I*. Weather-induced storage shocks are the instrumental variables for Henry Hub price that identify demand and are excluded in stage two. The first stage demand regression is:

$$ln(p_t) = \pi_{d0} + \gamma w_t + \Delta x_t + \delta \sum_{i=1}^{3} stor_{t-i} + \sum_{i=1}^{I} \rho_{di}\, t^i + \varepsilon_{dt}$$

Second and Third Stage

As in all 3SLS estimations, the second stage estimates the structural supply and demand equations (1) and (2) with predicted values of price from the first stage. In the third stage, residuals from the second stage are used to estimate the variance-covariance matrix. Then, an FGLS regression of quantity on the original independent variables including non-fitted price and using standard GLS weights is performed. This allows 3SLS, unlike 2SLS, to exploit the correlation of the disturbances across equations. This improves efficiency and also accounts for heteroskedasticity.

Identification of Supply

In order for elasticity of supply estimate β_s to be unbiased and consistent, current month weather shocks must shift demand and be uncorrelated with any unobserved shifts in supply. Weather is ideal since it shifts demand but producers cannot influence or predict it beyond the rough estimates provided by seasonal climate normals. Furthermore, weather patterns are unlikely to be correlated with general economic conditions, technological changes or other unobserved shifts in production capacity.

An additional concern is that weather shocks may sometimes be correlated with hurricanes. Hurricanes often disrupt the supply of natural gas from the Gulf of Mexico and cause prices to spike. To account for this, a control is included for duration and severity of hurricane supply disruptions in the last decade. As would be expected, including these variables decreases the magnitude of estimates but also decreases the standard errors. Additionally, oil price is included in the regression in order to soak up adjustments in production capacity that may be caused by capital reallocations.

Identification of Demand

The most novel facet of the estimation strategy employed in this paper is the use of lagged weather-induced storage shocks to identify demand. The intuition is that a weather-related rise or fall in storage levels constitutes a shift in future supply that can be used to identify short-run demand.

The IV exclusion restriction requires that weather-induced storage shocks have zero covariance with unobserved demand shifters in the current month. In particular, there is a concern that weather factors are correlated over time. This is discussed in detail in the *Methodological Concerns* section but is largely mitigated by the fact that current month weather shocks are already included in the demand equation. The identification assumption is that, after controlling for current weather, lagged weather-induced storage shocks are only related to current demand through their effect on expected price.

Data and Descriptive Statistics

Data for U.S. production, consumption, storage and price series of natural gas are from the U.S. Energy Information Administration (EIA) Natural Gas database. The data include total US production and consumption broken down by consumer type: Residential, commercial, industrial, electricity generation, and vehicle fuel. The data also include the quantities of natural gas injections and withdrawals from storage and total imports and exports for the US. There are several price series including average wellhead prices, city gate prices and daily Henry Hub spot prices along with NYMEX futures prices for 1, 2, 3 and 4 month futures contracts. In this paper all production, consumption, storage and price data series are aggregated by month for the entire US. Storage, production, Henry Hub price and residential and commercial gas use data exists from 1980 to 2010. Futures prices exist from 1994 onward and industrial, gas vehicle and electricity generator consumption data exists from 2001 to 2010. The EIA also publishes data on variables such as Cushing crude oil prices and oil related variables which can be found in the Petroleum & Other Liquids database.

U.S. weather data are from the National Oceanic and Atmospheric Administration NOAA. Variables are the U.S. monthly HDD and CDD along with the climate normals; the thirty year month-specific averages. HDD and CDD values are weighted by population in order to better predict total energy use.

Instruments are constructed from the weather and storage variables. Weather shocks are calculated as the observed deviations in HDD and CDD from the monthly climate normal. Weather shocks are summed over the previous three months in order to utilize only large cumulative shocks. Similarly, storage shocks are calculated as the observed deviations from thirty year month-specific averages. Fitted values from a regression of storage shocks on weather shocks are then used to represent weather-induced storage shocks.

Hurricane data is collected from the National Hurricane Center. Their website, maintained by the National Weather service, provides the names, dates and locations of hurricanes that have hit the US. Data specific to which hurricanes caused natural gas supply disruption as well as the magnitude and duration of each disruption is detailed in an a public report submitted to The Energy Foundation by *Energy and Environmental Analysis, Inc.* in a report titled "Hurricane Damage to Natural Gas Infrastructure and Its Effect on the U.S. Natural Gas Market."

Figures 16 – 21 in the *Tables and Figures* section display a number of industry trends for aggregate production, storage and consumption of natural gas. Figure 16 reveals that production is relatively stable at the beginning of the sample period and begins increasing at a high rate in the second half of the decade. This fact is mirrored by an increase in the number of wells drilled, shown in Figure 17. The sharp increase in new wells is largely due to improvements in fracking and horizontal drilling technology. Figure 18 demonstrates the pronounced seasonal consumption patterns; highest in the winter (November, December, January, and

February) and lowest during the shoulder months with a second, smaller uptick in warm summer months. Figure 19 shows how storage levels change both seasonally and in aggregate over the sample period. Figure 20 shows consumption over the sample. The series demonstrates both the seasonal component and a moderate aggregate increase in demand over time. Figure 21 displays Henry Hub spot price. The volatility of the price series, in comparison with consumption, suggests the inelastic nature of demand.

Results

Table 1 presents the first stage regression results. Weather shocks and weather-induced storage shocks have the expected signs and are all statistically significant. HDD and CDD shocks increase price; the sum of three months, weather-induced storage shocks decreases price.

Table 1 First Stage Results for Demand and Supply Equations

FIRST STAGE: LN(HENRY HUB PRICE)	
3 Month Storage Shock Weather-induced (100MMcf)	-0.0279*** (0.007)
HDD Weather Shock w_t (100 HDD)	0.14*** (0.04)
CDD Weather Shock w_t (100 CDD)	0.23** (0.1)
Hurricane Disruption (MMcf-days)	0.4 (0.3)
LN(Crude Price)	0.85*** (0.09)
Net imports (100MMcf)	0.13* (0.07)
Observations	120
Time Trend I	3
Adj R-squared = 0.75	
F STAT = 34.13	

Results from the two and three-stage least squares regressions are displayed in table 2. The estimates of the elasticity of supply and demand are the coefficients on Henry Hub spot price, p_t, in the supply and demand equations. Column (1) displays OLS estimates for comparison with the preferred specifications. Column (2) displays two-stage least squares estimates and the remaining columns (3) – (6) present three-stage least squares estimates. Columns (3) - (6) differ by the order of the polynomial time trend and by the inclusion of certain control variables.

Elasticity of supply estimates in Table 1 fall between 1.16 and 1.29. All estimates are significant at the 1% level. By contrast, the OLS estimate of supply elasticity is 0.32, much smaller in magnitude and substantially different from all instrumented estimates. Bias is in the expected direction. If unobserved shifts in supply are negatively correlated with price, as is typical, then OLS should generate more inelastic estimates. The preferred estimates are displayed in columns (4), (5) and (6). These columns employ three-stage least squares and include a 3rd order polynomial time trend. In addition, column (5) contains controls for net imports of natural gas and Cushing crude oil prices. Column (6) includes these and hurricane supply disruption. The estimated supply elasticity has smaller standard errors and is larger in magnitude when additional controls are included.

Demand elasticity is estimated separately using two different instruments, weather-induced storage shocks and gross storage shocks. Elasticity of aggregate demand estimates range from -0.14 to -0.19 for weather-induced storage shocks and from -0.11 to -0.14 for gross storage shocks. Not surprisingly, standard errors are larger when instrumenting with weather-induced storage shocks. These shocks are more credibly exogenous but somewhat weaker predictors of Henry Hub price than gross storage shocks. The OLS estimate of demand elasticity is -0.049, meaningfully smaller and more inelastic than the instrumented estimates. Again, bias is in the expected direction. If unobserved shifts in demand are positively correlated with price, as is typical, then OLS should generate more inelastic estimates in demand. Clearly, bias in the uninstrumented estimates is substantial, especially on the supply side. This is intuitive since shifts in supply were larger and more frequent than shifts in demand in the years studied. Accordingly, more substantial bias due to price endogeneity would be expected on the OLS supply-side estimates.

Table 2 Demand and Supply of Natural Gas

	OLS	2SLS	3SLS	3SLS	3SLS	3SLS
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
Quantity Delivered			**Demand**			
Instrumenting for expected price with weather-induced storage shocks						
Henry Hub Price	-0.049**	-0.19*	-0.176*	-0.189*	-0.14***	-0.15***
p_t	(0.022)	(0.11)	(0.10)	(0.11)	(0.06)	(0.06)
HDD	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***
Pop. weighted	(.00002)	(.00003)	(.00003)	(.00003)	(.00002)	(.00002)
CDD	0.0008***	0.0008***	0.0009***	0.0009***	0.0009***	0.0008***
Pop. weighted	(.00007)	(.00009)	(.00007)	(.00007)	(.00006)	(.00007)
Instrumenting for expected price with gross storage shocks						
Henry Hub Price	-0.049**	-0.14**	-0.13**	-0.14**	-0.12***	-0.11***
p_t	(0.022)	(0.06)	(0.05)	(0.06)	(0.04)	(0.04)
			Supply			
Instrumenting for Henry Hub spot price with HDD and CDD weather shocks						
Henry Hub Price	0.32***	1.16***	1.27***	1.16***	1.29***	1.27***
p_t	(0.075)	(0.32)	(0.36)	(0.31)	(0.22)	(0.21)
Ln(storage$_{t-3}$)	1.7e-07***	2.6e-07**	2.9e-07**	2.6e-07**	3.9e-07***	3.7e-07***
Past three months	(6.3e-08)	(1.3e-07)	(1.4e-07)	(1.2e-07)	(1.0e-07)	(1.0e-07)
Additional Controls						
Net exports	Yes	No	No	No	Yes	Yes
*Hurricane shut ins**	Yes	No	No	No	No	Yes
Crude oil price	Yes	No	No	No	Yes	Yes
** supply equation only*						
Observations	120	120	120	120	120	120
Time Trend I	3	3	2	3	3	3
R-squared Supply	0.29					
R-squared Demand	0.95					

Notes: The dependent variable is the total monthly quantity of natural gas delivered to consumers. For **demand**, coefficients on Henry Hub price are estimates of demand elasticity. This table displays estimates when both *gross storage shocks* and *weather-induced storage shocks* are used as instruments. For **supply**, coefficients on Henry Hub Price are estimates of supply elasticity. Columns (1)-(6) vary by the estimation method, types of controls and the order of the polynomial time trend included. All columns except (3) include a 3rd order polynomial time trend. Column (1) presents the OLS estimates with no IVs. All columns include a control on the RHS for the quantity of gas in storage. Controlling for storage levels increases the strength of the correlation between current month weather, HDD and CDD and Henry Hub price. Monthly data covers the time span from January 2001 through December 2010. Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 presents estimates of demand for different natural gas consumer types. Elasticity of demand is compared for commercial, residential, industrial, and electrical consumers as well as for natural gas vehicles. The models use Henry Hub price and again compare estimates from both instruments on the demand side. Estimates of supply are consistent across all specifications.

Table 3 Demand by Consumer Type

	Model				
	3SLS	3SLS	3SLS	3SLS	3SLS
VARIABLES	(1) Commercial Quantity Demanded	(2) Residential Quantity Demanded	(3) Industrial Quantity Demanded	(4) Electricity Quantity Demanded	(5) Vehicle Quantity Demanded
Instrument with weather-induced storage shocks					
Elasticity of Demand					
Ln(Henry Hub)	-0.30***	-0.46***	-0.20***	-0.21***	0.12**
p_t	(0.097)	(0.14)	(0.067)	(0.07)	(0.05)
Elasticity of Supply	1.27***	1.27***	1.27***	1.28***	1.28***
p_t	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)
Instrument with gross storage shocks					
Elasticity of Demand					
Ln(Henry Hub)	-0.32***	-0.56***	-0.13***	-0.17***	0.18***
p_t	(0.06)	(0.11)	(0.04)	(0.05)	(0.05)
Elasticity of Supply	0.98***	0.98***	0.99***	0.98***	0.99***
p_t	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Observations	120	120	120	120	120
Time Trend I	3	3	3	3	3

Notes: The dependent variable for both the supply and demand equations is the total monthly quantity of natural gas delivered to consumers. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Estimates for commercial demand elasticity are -0.30 and -0.32 and significant at the 1% level. As expected, standard errors are larger when estimating with the less precise instrument, weather-induced storage shocks. Estimates for residential demand represent demand by utilities and LDCs rather than actual residential consumption at the burner tip. Utilities and LDC's maintain the largest private storage capacity of all consumer types. It is, therefore, not surprising that residential demand estimates are the largest in the sample -0.46 and -0.56; these estimates are also significant at the 1% level. All estimates are significant at the 1% level and standard errors are smaller when using the more precise instrument.

Estimates of industrial demand are the most inelastic at -0.20 and -0.13 and significant at the 1% level. Industrial consumers own a smaller percentage of private storage capacity than either residential or commercial consumers. Demand for their products (e.g. gypsum, cement, industrial chemicals) is highly dependent on macroeconomic factors and for these reasons might be expected to be the most inelastic consumer type. On the other hand, industrial consumers are often more likely than other consumers to be able to switch between fuel types in response to high prices. It is thus unclear, a priori, whether industrial consumers should be much more or only a little more inelastic than other consumer types.

Estimates of electricity generation demand for natural gas are -0.17 and -0.21 and significant at the 1% level. Estimates of natural gas vehicle demand elasticity diverge from the other consumer types. Demand estimates are positive and significant at 0.12 and 0.18. While gas consumption by vehicles is certainly likely to be inelastic and perhaps close to zero, this result remains somewhat surprising. It seems possible, however, that gas consumption by vehicles may have more to do with the price differential between gasoline and natural gas than the price of natural gas alone. If natural gas price increases have tended to coincide with much larger increases in gasoline prices, then omitted variable bias resulting from the exclusion of gasoline prices may explain this result. Controlling for the price of crude oil, which is highly correlated with gasoline price, and using year fixed effects does result in the demand estimates becoming negative or smaller in magnitude where still positive. Supply estimates in all these models range from 0.9 and 1.28 similar to previous estimates.

Robustness

A number of robustness checks are run in order to test the sensitivity of parameter estimates to the model specification. In the first set of tests, the models are re-estimated with year fixed effects in order to determine whether elasticity estimates are sensitive to the structure of the time variables. Table 4 in the *Tables and Figures* section displays the simultaneous equation results when year fixed effects are substituted in place of a polynomial time trend. The elasticity coefficients are not meaningfully different from those estimated with a polynomial time trend. This shows that the specification is not particularly sensitive to different methods of controlling for the time trend.

Demand elasticity is re-estimated using only hurricane pipeline disruption as an instrument for price. The magnitude and duration of the disruption is used to construct the instrument. Hurricanes present an intuitive and less complex IV mechanism with which to estimate demand within a simultaneous equation framework. Their main drawback, from an econometric standpoint, is that they occur infrequently and are less significantly correlated with price in the first stage.

Table 5, in the *Tables and Figures* section, presents the results when only hurricane disruptions are used to instrument for price. The first stage results are presented at the bottom of the table. Hurricane disruption has an intuitive sign and a statistically significant correlation with price. Elasticity estimates by consumer type are all within two of their own standard errors of the primary estimates. Aggregate elasticity and the elasticity of electricity generators and industrial users are very close to the primary estimates. Standard errors are similar in size and coefficients are still significant at the 10% level. The estimates of commercial and residential utilities are substantially smaller and less precisely estimated, however. A possible explanation is that hurricanes occur only from June to November; when demand for heating is low or nonexistent. Since the instrument is a poor predictor of price during months of peak LDC gas usage, we might expect that it would estimate these elasticities imprecisely.

Finally, consumption quantity and Henry Hub price time series are tested for unit roots. Previous studies have used cointegration ECM approaches to estimate demand elasticities in natural gas. If the data used in this study is also cointegrated, a similar model could be estimated in order to compare the results. An ADF test with Elliot, Rothenberg and Stock critical values is run for both series. The null hypothesis of a unit root is rejected for the quantity variable. See Table 6 in the *Tables and Figures* section. Notably, the test does reveal a correlation between the current month and the 12 month lag. A clear indicator that consumption in a given month is correlated from one year to the next. The null hypothesis of a unit root cannot be rejected for the Henry Hub price; see Table 7 in the *Tables and Figures* section. ACF and PACF tests indicate that there is likely AR(1) or AR(2) type autocorrelation in the price variable. Since quantity and price do not share a common stochastic drift they are not cointegrated. Consequently, an ECM approach to provide comparable estimates and validate the instrumental variables approach is not possible for the sample period examined in this paper.

For additional consideration, price elasticity is estimated with NYMEX futures prices in the demand equation instead of Henry Hub price. NYMEX futures prices are considered because end users commit to receive some portion of the gas they consume with forward contracts. For this reason, demand may be more closely related to expected price rather than spot price. NYMEX futures price are used as a proxy of expected price. These results are included at the end of the *Tables and Figures* section. NYMEX price elasticities are slightly smaller in magnitude but not substantially different from than those estimated with Henry Hub prices. The conclusion drawn in this paper is that Henry Hub price and NYMEX futures prices are similarly useful measures for estimating demand elasticity. This is not surprising since natural gas spot and near-term futures prices are strongly correlated.

Table 8 presents results of different model specifications using the 3-month NYMEX futures price in place of Henry Hub; this table is directly comparable to Table 2 in the *Results* section. Table 9 presents aggregate elasticity estimates using 1, 2, 3 and 4-month NYMEX futures prices; results in this table are most directly comparable to column (6) in Table 2. Table 10 displays elasticity estimates of different consumer types using 1, 2, 3 and 4-month NYMEX futures prices; this table is comparable to Table 3 in the *Results* section. Tables 8, 9 and 10 are found at the end of the *Tables and Figures* section.

Conclusions

The primary objective of this paper is to demonstrate that weather shocks can be used as instruments for price in a 3SLS estimation framework to produce unbiased estimates of both supply and demand of natural gas. The influence of weather on demand in this industry is well acknowledged. In spite of this, it has rarely been used as an instrumental variable in natural gas models and then only for estimation of the supply curve. This paper shows how weather-induced storage shocks can be used to generate relatively precise estimates of short-run demand. Most importantly, this framework presents an effective way to address price endogeneity in both supply and demand estimation; an issue which has often been ignored in previous work. Ultimately, the ability to credibly estimate causal parameters for both supply and demand means that the estimates can be used to forecast short-run price movements based on expected shifts in supply or demand.

A second objective of this paper was to extend the general estimation method utilized in agriculture by Roberts and Schlenker (2013) to a different, but similar-enough commodity market. The robustness of the method across commodity markets similar in key respects, yet still as diverse as agriculture and natural gas, implies that it may be applicable in other storage-dependent, weather-influenced industries. Additional commodity markets with potential for successful application of this estimation method include oil, gas liquids and agricultural products such as cocoa and coffee.

The model generates elasticity estimates of short-run demand and supply in the post deregulation, shale gas era, from 2000 to 2010. Aggregate U.S. natural gas elasticity during this time ranges from -0.19 to -0.28 across model specifications. Elasticity varies by consumer type with industrial users the most inelastic ranging from -0.13 to -0.21 and residential utilities the most relatively elastic, ranging from -0.38 to -0.56 across specifications; commercial utilities range from -0.21 to -0.32. Electricity generators exhibit an elasticity ranging from -0.17 to -0.28. Natural gas vehicles demonstrate positive and significant demand elasticity. These estimates may be biased due to the omission of gasoline prices or other variables that account for different usage patterns in natural gas automobiles. The estimates of short-run supply elasticity range from 0.98 to 1.28, implying that producers exhibit something near unit elasticity.

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Additional Tables and Figures

Figure 1

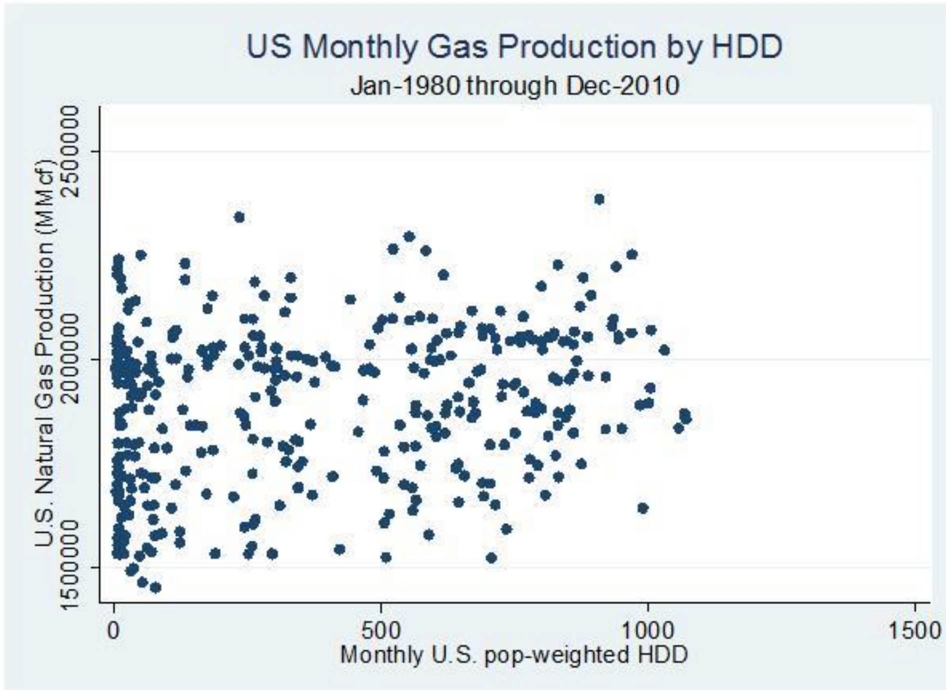
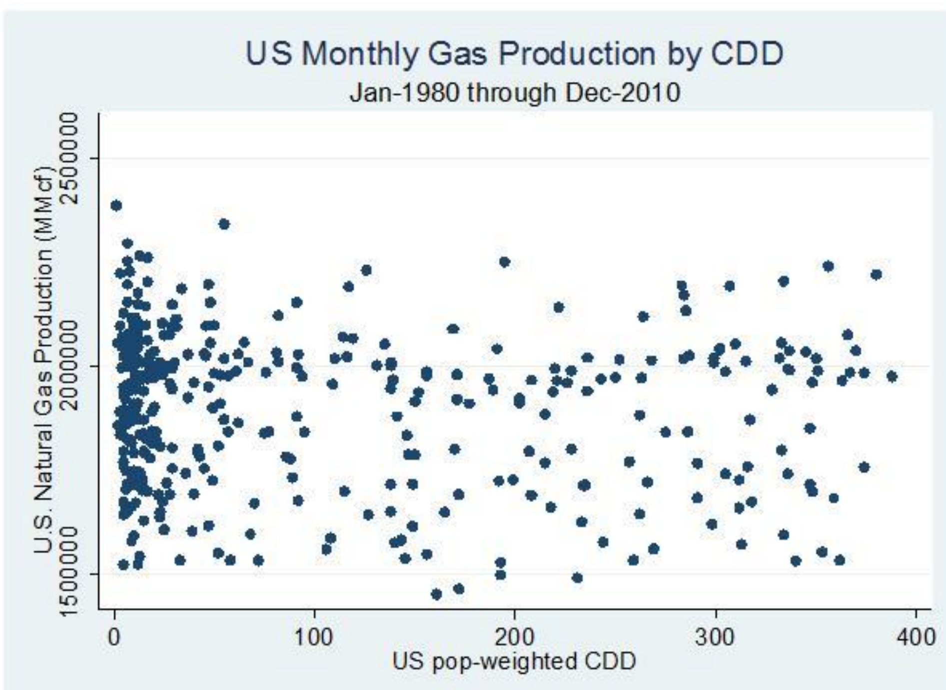


Figure 2



Notes: Top panel plots monthly gas production on monthly U.S. HDD (heating degree days). Bottom level plots monthly gas production on the y-axis on monthly U.S. CDD (cooling degree days). HDD and CDD have predictable seasonal variation and the lack of correlation shows there is no systematic, seasonal (and endogenous) production response to seasonal weather variation.

Figure 3

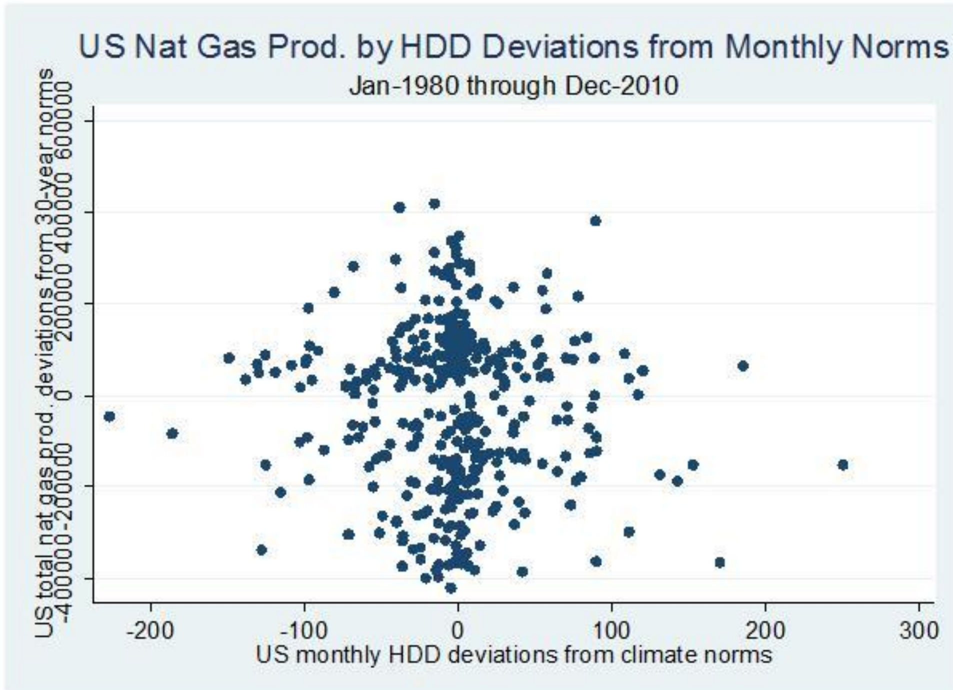
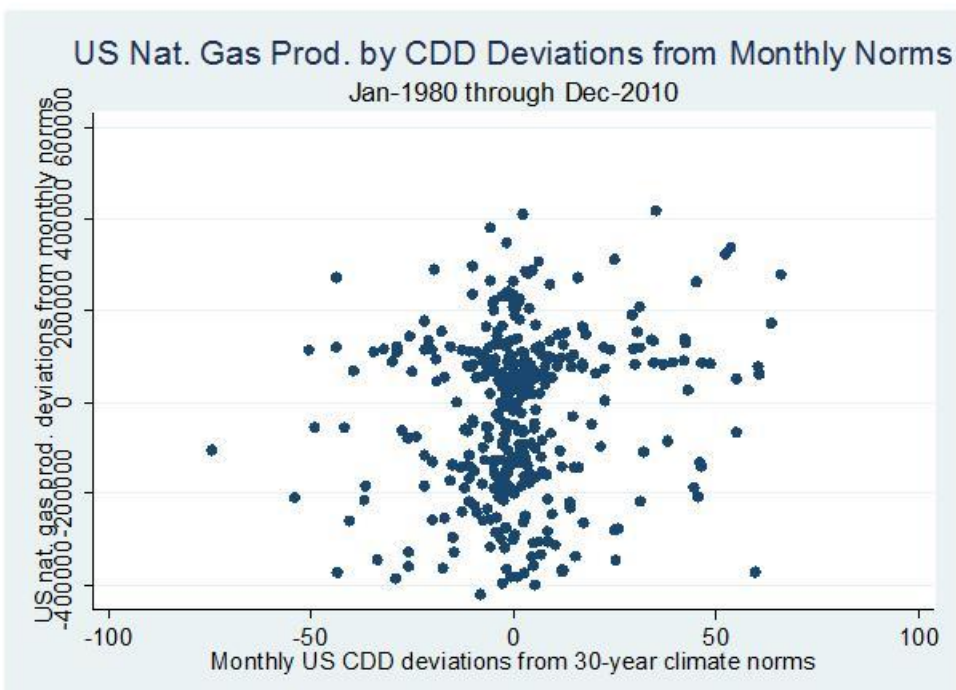


Figure 4



Notes: Top panel plots deviations from month-specific average gas production on deviations in HDD from monthly climate normals. Bottom level plots deviations from month-specific average gas production on deviations in CDD from monthly climate normals. Lack of correlation shows there is no systematic, instantaneous (and endogenous) production response to weather shocks.

Figure 5

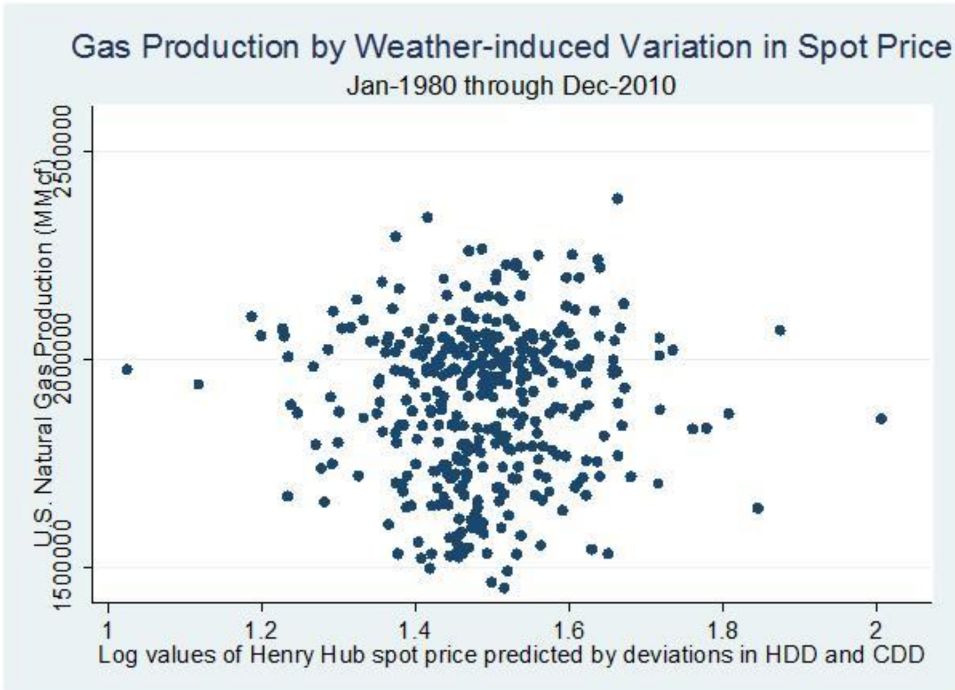
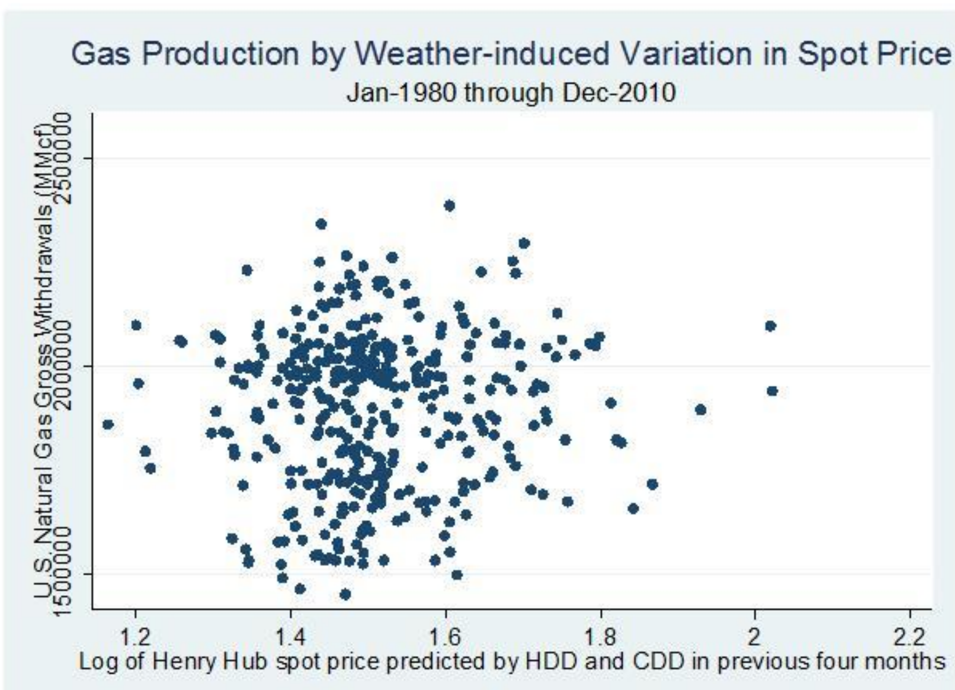


Figure 6



Notes: Top panel plots gas production on the Henry Hub spot price predicted by current month weather. Bottom panel plots gas production on the Henry Hub spot price predicted by weather in the previous four months. This demonstrates that production is not endogenous to the fluctuation in spot prices caused by weather.

Figure 7

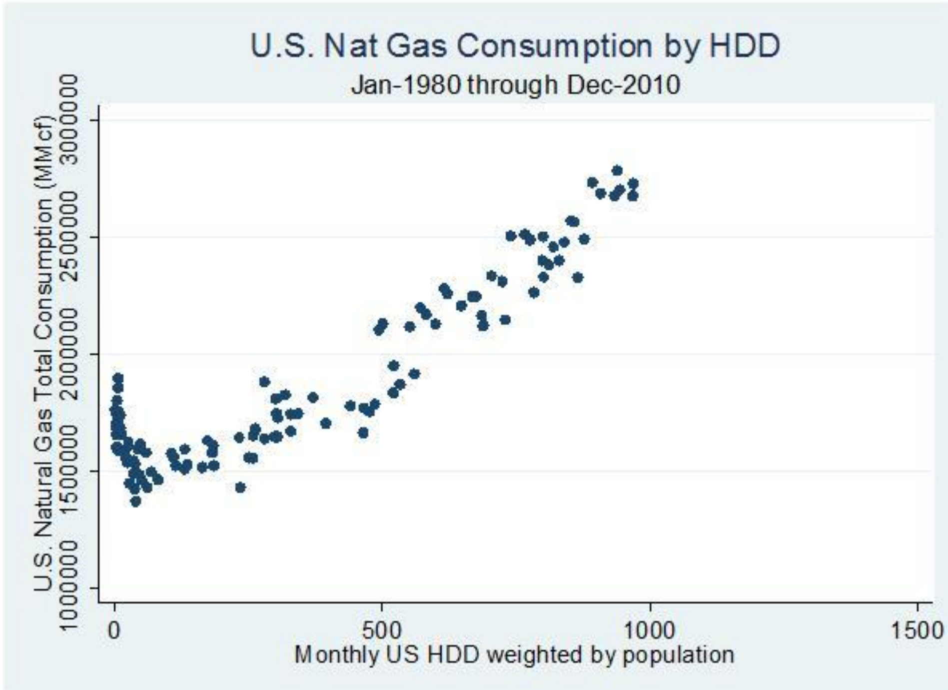
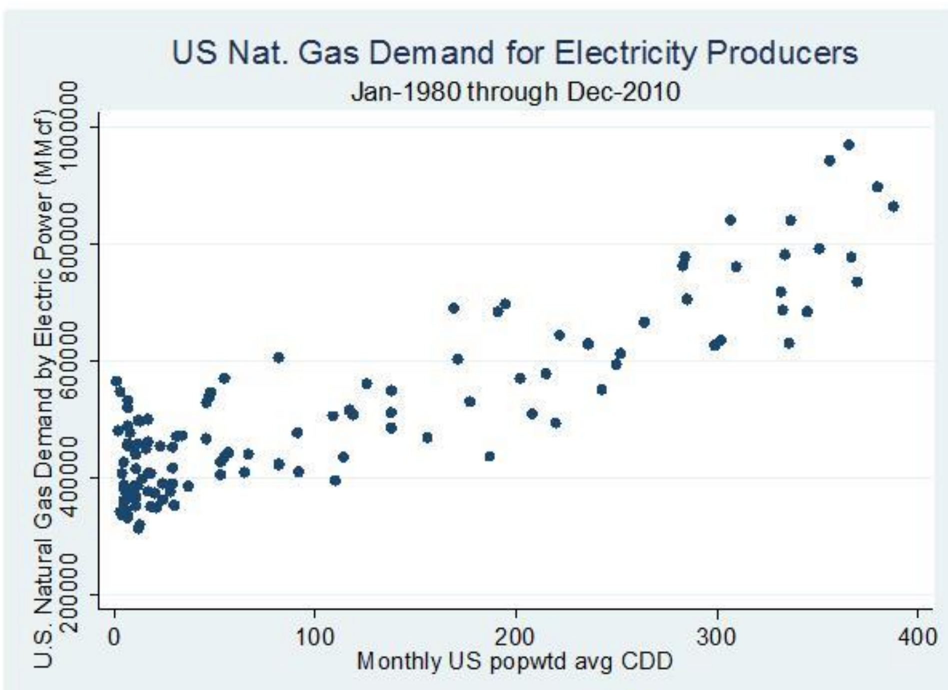


Figure 8



Notes: Top panel plots total U.S. gas consumption on HDD. Bottom panel plots gas consumption by electricity generators on CDD. These show a clear relationship between consumption and weather.

Figure 9

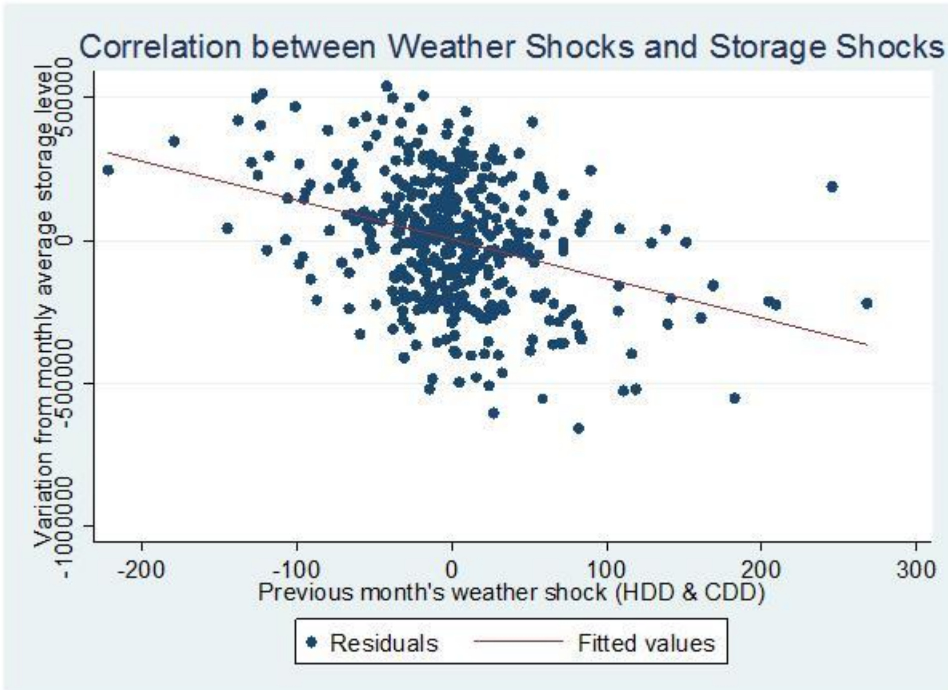
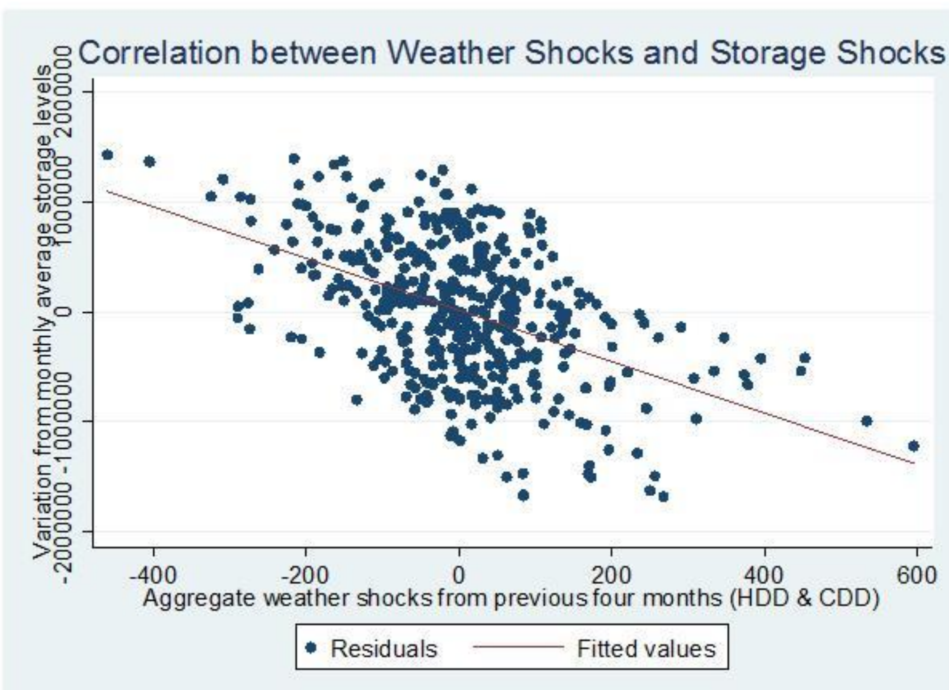


Figure 10



Notes: Top panel plots storage shocks on the previous month's weather shocks and includes a fitted line. Bottom panel plots storage shocks on the sum of the previous four months' weather shocks and includes a fitted line. These scatter plots reveal the correlation between weather and storage levels; a key relationship link in the identification strategy of demand elasticities.

Figure 11

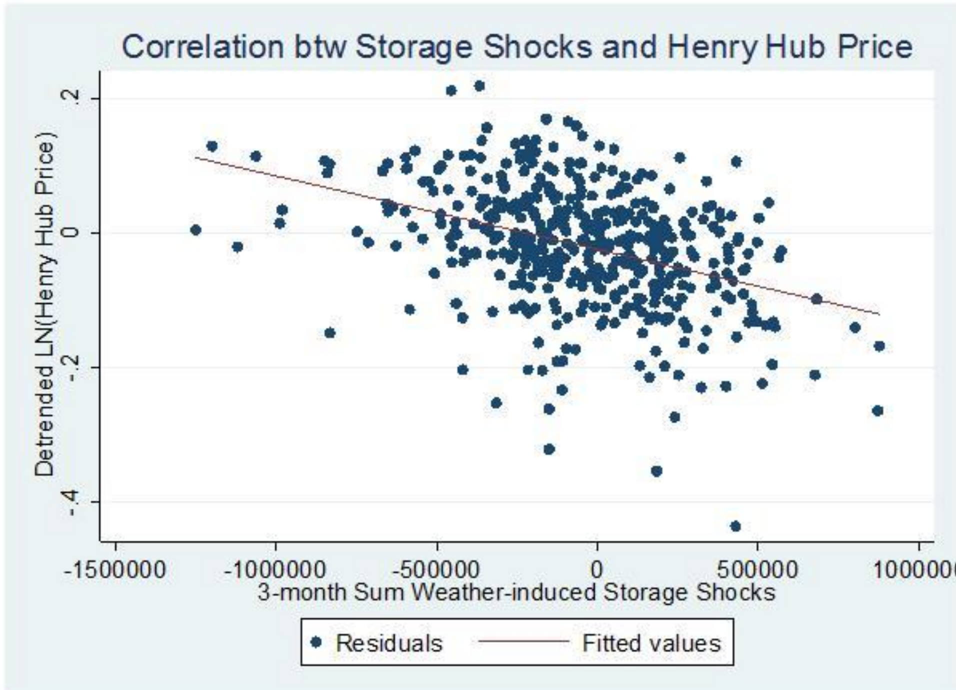
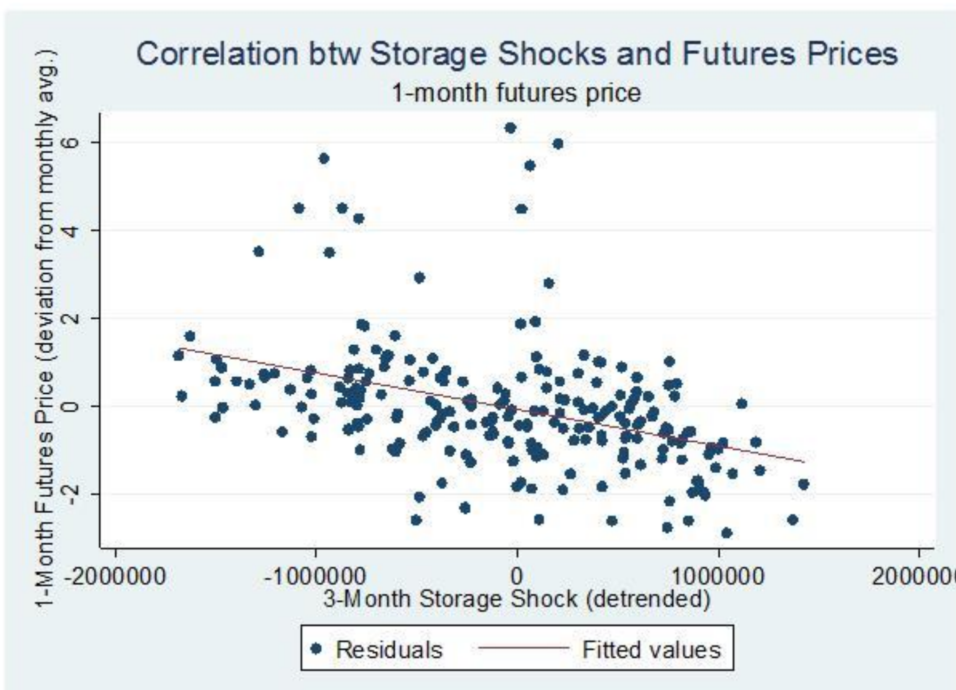


Figure 12



Notes: Figures 11 shows the relationship between Henry Hub price and storage shocks. Figure12 shows the relationship between 1-month NYMEX futures prices and storage shocks. The storage shock used is the sum of the last three months' storage shocks. Fitted lines are included to emphasize the downward sloping trend; storage build-ups are correlated with lower futures prices while storage draw-downs are correlated with higher futures prices.

Figure 13

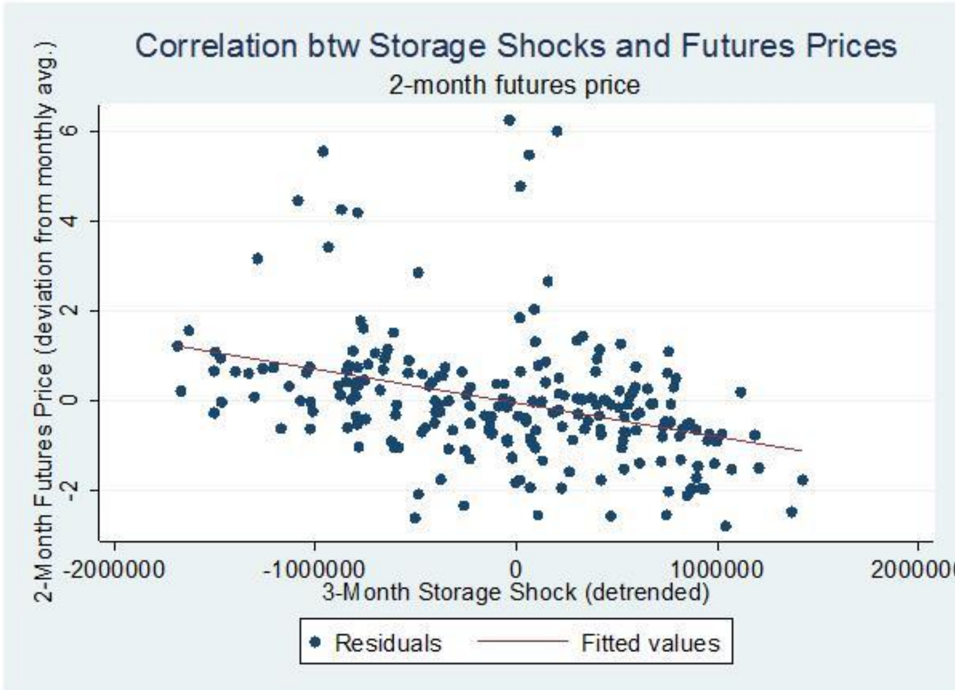
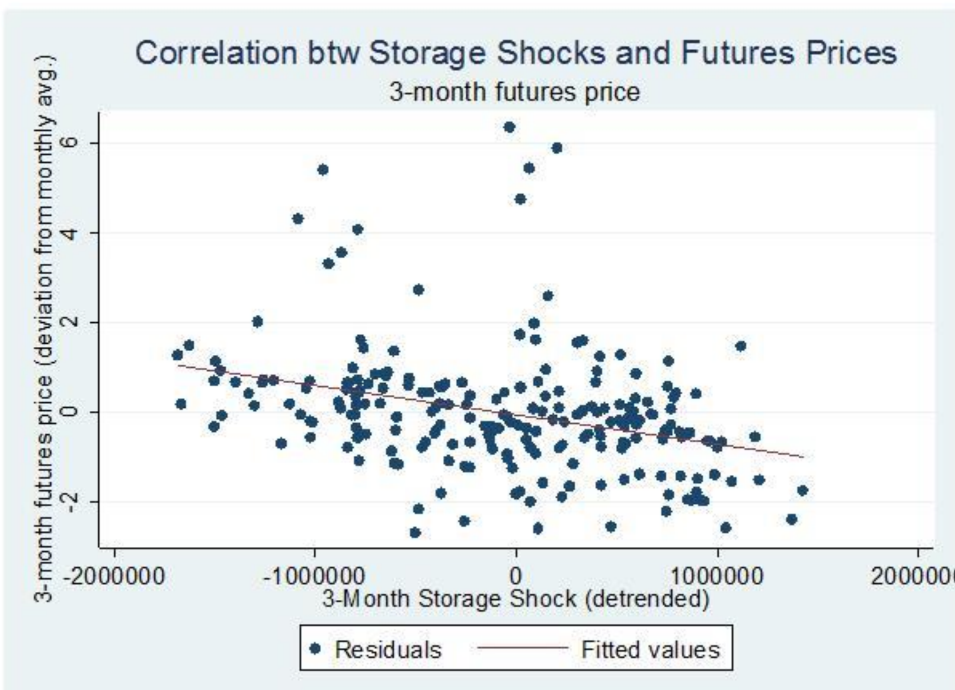
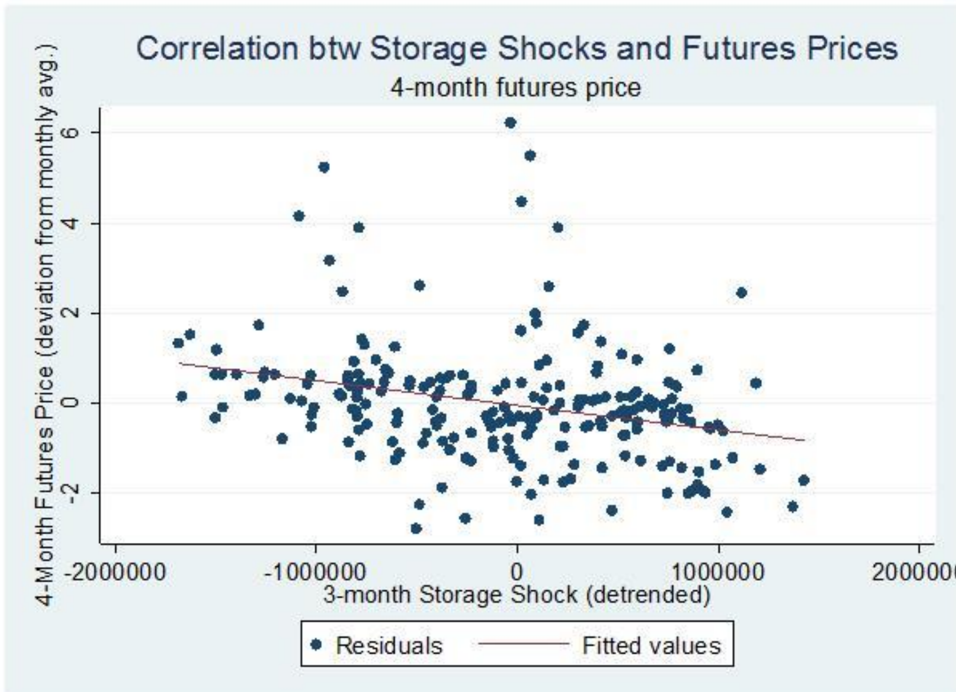


Figure 14



Notes: Figure 13 and 14 show the relationship between 2-month and 3-month NYMEX futures prices and storage shocks. The storage shock used is the sum of the last three months' storage shocks. Fitted lines are included to emphasize the downward sloping trend; storage build-ups are correlated with lower futures prices while storage draw-downs are correlated with higher futures prices.

Figure 15



Notes: Figure 15 shows the relationship between 4-month NYMEX futures prices and storage shocks. The storage shock used is the sum of the last three months' storage shocks. Fitted lines are included to emphasize the downward sloping trend; storage build-ups are correlated with lower futures prices while storage draw-downs are correlated with higher futures prices.

Figure 16

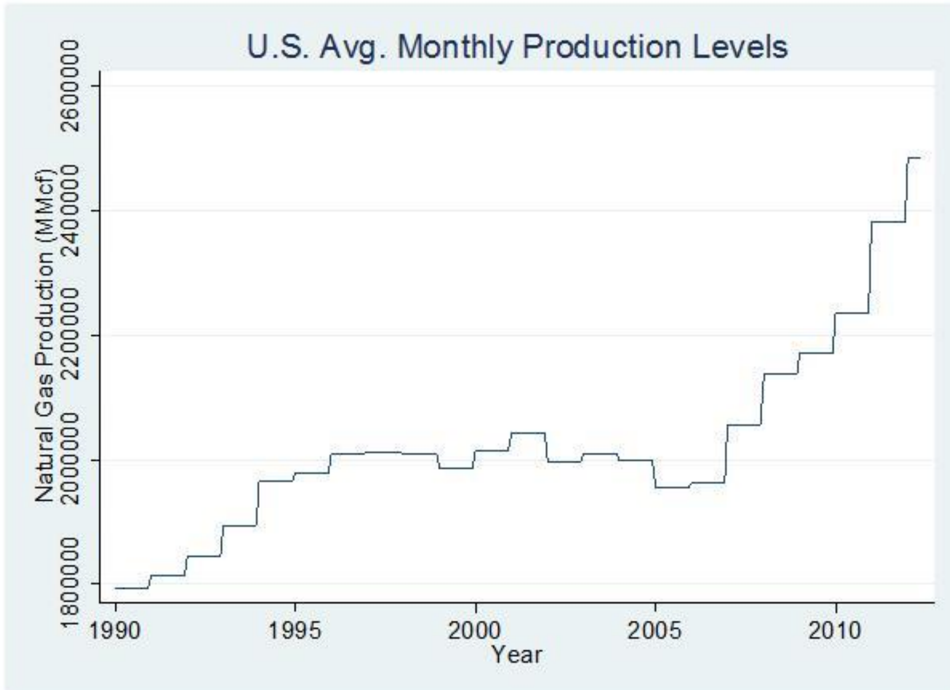
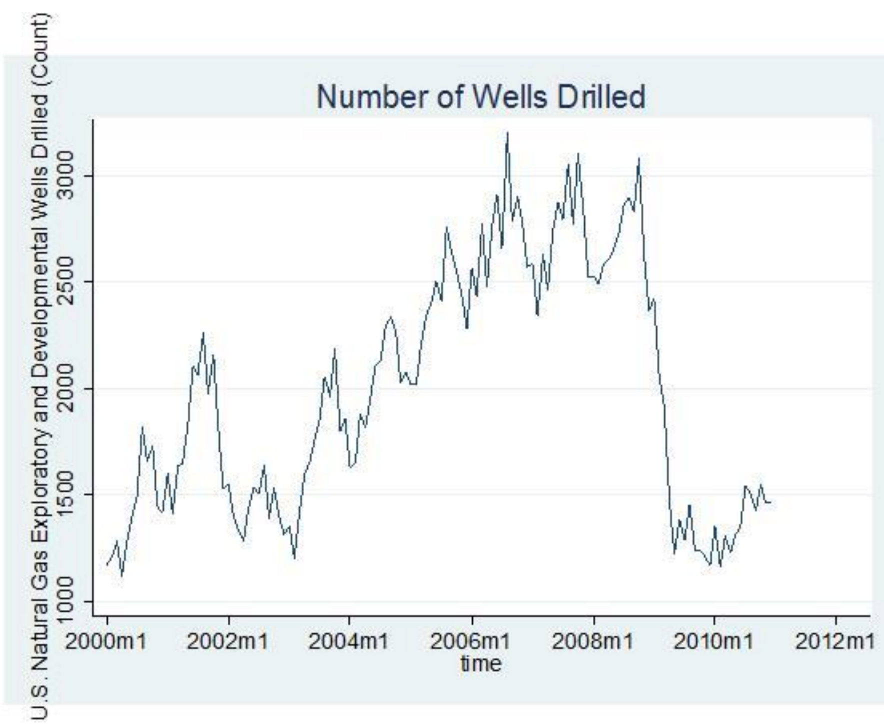


Figure 17



Notes: Figures 16 and 17 illuminate general trends in production over the sample. Figure 16 shows the upward trend in production since 1990. Figure 17 shows a corresponding increase in the number of developmental and exploratory wells drilled.

Figure 18

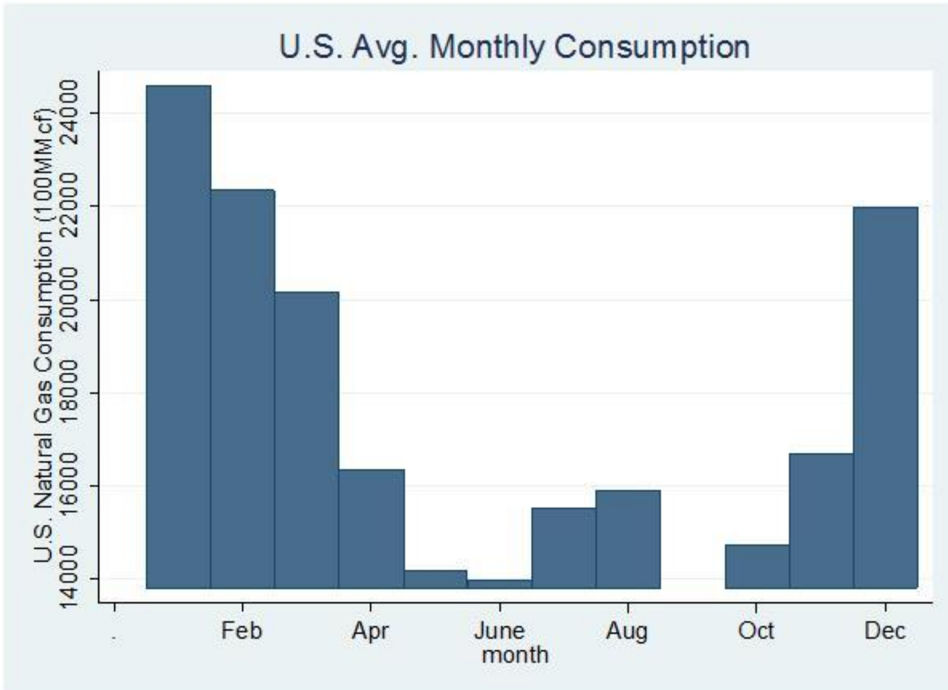
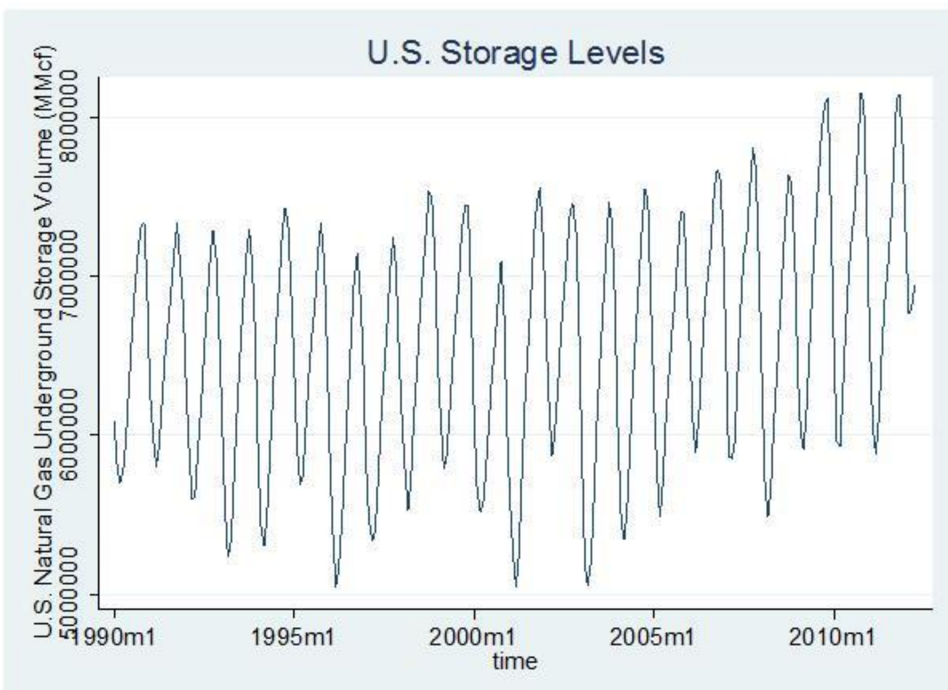


Figure 19



Notes: Figures 18 and 19 illuminate general trends in consumption and storage over the sample. Figure 18 shows the average monthly consumption. Consumption peaks in winter months and again during July and August. Figure 19 shows storage levels of natural gas.

Figure 20

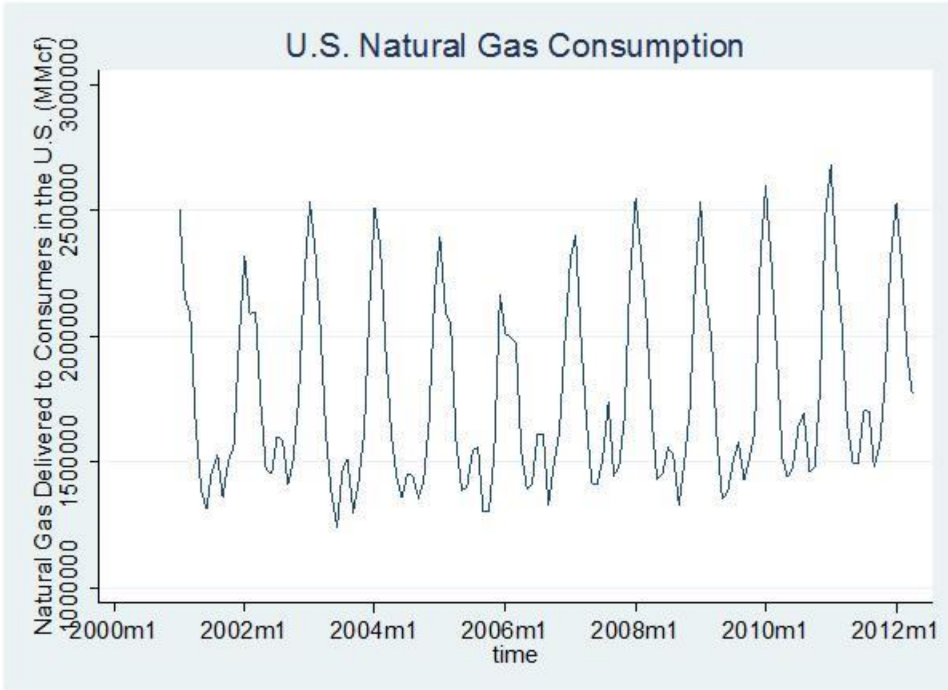
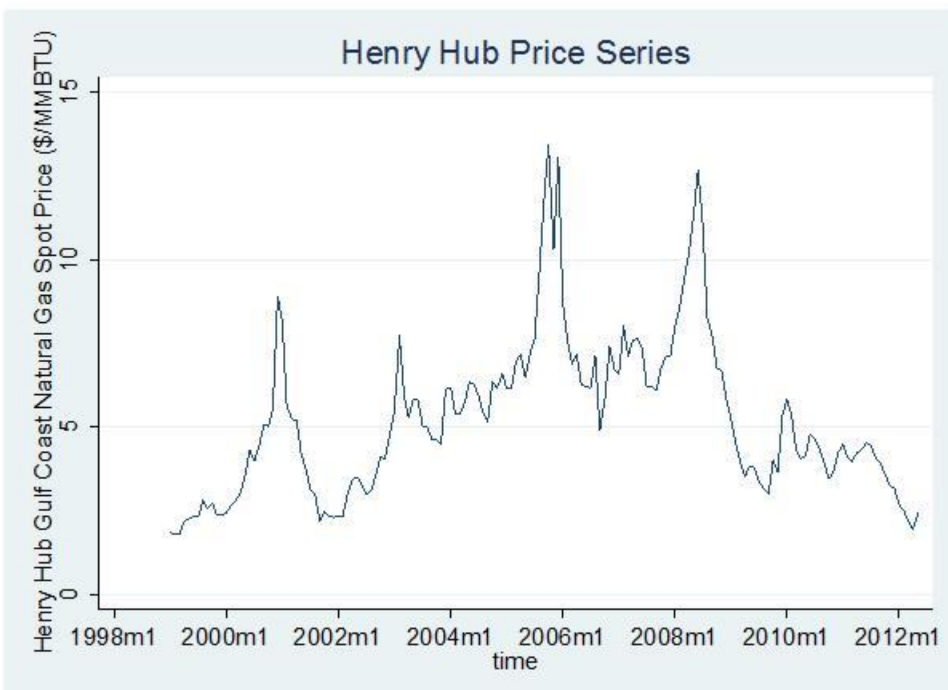


Figure 21



Notes: Figures 20 and 21 illuminate general trends in price and consumption over the sample. Figure 20 shows both the seasonal nature of consumption along with the moderate increase in demand that occurred over the sample. Figure 21 shows the Henry Hub price series. The high volatility of price relative to consumption suggests that demand is inelastic.

Table 4 Year fixed effects used instead of a 3rd order polynomial time trend

	Model				
	3SLS	3SLS	3SLS	3SLS	3SLS
VARIABLES	(1) Commercial Quantity Demanded	(2) Residential Quantity Demanded	(3) Industrial Quantity Demanded	(4) Electricity Quantity Demanded	(5) U.S. Total Quantity Demanded
	Instrument with weather-induced storage shocks				
Ln(Henry Hub) w/Yr Fixed Effects	-0.21**	-0.389*	-0.21**	-0.23	-0.198**
	(0.14)	(0.23)	(0.10)	(0.17)	(0.10)
Ln(Henry Hub) w/poly time trend	-0.30***	-0.46***	-0.20***	-0.21***	-0.15***
	(0.097)	(0.14)	(0.067)	(0.07)	(0.06)
Elasticity of Supply	1.28***	1.28***	1.28***	1.28***	1.28***
p_t	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
	Instrument with gross storage shocks				
*Ln(Henry Hub)*** w/Yr Fixed Effects*	-0.25**	-0.479**	-0.20***	-0.28**	-0.28**
	(0.12)	(0.20)	(0.07)	(0.14)	(0.14)
Ln(Henry Hub) w/poly time trend	-0.32***	-0.56***	-0.13***	-0.17***	-0.11***
	(0.06)	(0.11)	(0.04)	(0.05)	(0.04)
Elasticity of Supply	1.06***	1.06***	1.06***	1.06***	1.06***
p_t	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
Observations	120	120	120	120	120
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Trend					

Notes: The dependent variable for both the supply and demand equations is the total monthly quantity of natural gas delivered to consumers. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5 Demand by Consumer Type Using Only Hurricane Shocks to Instrument for Price

	Model				
	3SLS	**3SLS**	**3SLS**	**3SLS**	**3SLS**
VARIABLES	(1) Commercial Quantity Demanded	(2) Residential Quantity Demanded	(3) Industrial Quantity Demanded	(4) Electricity Quantity Demanded	(5) Total Quantity Demanded
Instrument with hurricane shocks only					
Ln(Henry Hub Price)	-0.06	-0.18	-0.27***	-0.257**	-0.13*
p_t	(0.12)	(0.13)	(0.09)	(0.12)	(0.07)
Observations	120	120	120	120	120
Time Trend I	3	3	3	3	3
First-stage of hurricane shocks regression					
Hurricane disruption	0.88**	0.88**	0.88**	0.88**	0.88**
(MMcf-days)	(0.41)	(0.41)	(0.41)	(0.41)	(0.41)

Notes: The dependent variable for both the supply and demand equations is the total monthly quantity of natural gas delivered to consumers. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6. DF-GLS UNIT ROOT TEST

VARIABLE				
Ln(Quantity)		*Critical Value*		
Lags	*DF-GLS tau Test Statistic*	1%	5%	10%
12	-1.920	-3.537	-2.794	-2.519
11	-2.523	-3.537	-2.815	-2.538
10	-1.802	-3.537	-2.836	-2.558
9	-1.422	-3.537	-2.856	-2.576
8	-1.751	-3.537	-2.875	-2.594
7	-2.804	-3.537	-2.893	-2.611
6	-3.090	-3.537	-2.911	-2.627
5	-3.974	-3.537	-2.928	-2.643
4	-3.649	-3.537	-2.944	-2.657
3	-3.801	-3.537	-2.958	-2.671
2	-4.744	-3.537	-2.972	-2.683
1	-6.368	-3.537	-2.984	-2.694

Test uses Elliot, Rothenberg and Stock (1996) critical values

Table 7. DF-GLS UNIT ROOT TEST

VARIABLE				
Ln(Henry Hub)		*Critical Value*		
Lags	*DF-GLS tau Test Statistic*	1%	5%	10%
12	-1.166	-3.521	-2.803	-2.527
11	-1.275	-3.521	-2.822	-2.544
10	-1.204	-3.521	-2.840	-2.561
9	-1.157	-3.521	-2.858	-2.578
8	-1.672	-3.521	-2.875	-2.594
7	-1.810	-3.521	-2.891	-2.609
6	-1.939	-3.521	-2.907	-2.623
5	-1.776	-3.521	-2.922	-2.636
4	-1.934	-3.521	-2.936	-2.649
3	-1.686	-3.521	-2.949	-2.661
2	-1.684	-3.521	-2.961	-2.672
1	-1.541	-3.521	-2.972	-2.682

Test uses Elliot, Rothenberg and Stock (1996) critical values

Table 8 Demand and Supply of Natural Gas with NYMEX Futures prices

This table is most directly comparable to Table 2 in the *Results*

	Model					
	OLS	**2SLS**	**3SLS**	**3SLS**	**3SLS**	**3SLS**
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
Quantity Delivered			**Demand**			
Instrumenting for expected price with gross storage shocks						
Ln(Futures_3mo)	-0.07***	-0.14***	-0.14***	-0.13***	-0.13***	-0.11***
$E[p_t \mid_{t-3}]$	(0.016)	(0.032)	(0.03)	(0.03)	(0.02)	(0.02)
Instrumenting for expected price with weather-induced storage shocks						
Ln(Futures_3mo)	-0.08***	-0.21***	-0.26***	-0.24**	-0.21***	-0.23***
$E[p_t \mid_{t-3}]$	(0.017)	(0.07)	(0.10)	(0.10)	(0.06)	(0.07)
HDD	0.0009***	0.0009***	0.001***	0.001***	0.0009***	0.0009***
Pop. weighted	(.00002)	(.00002)	(0.00002)	(0.00002)	(.00002)	(.00002)
CDD	0.0009***	0.0009***	0.001***	0.001***	0.0009***	0.0008***
Pop. weighted	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)
			Supply			
Instrumenting for Henry Hub spot price with HDD and CDD weather shocks						
Henry Hub Price	0.225***	1.03***	1.028***	1.07***	0.94***	0.83***
p_t	(0.05)	(0.19)	(0.18)	(0.19)	(0.11)	(0.10)
$Ln(storage_{t-3})$	0.33***	0.38***	0.44***	0.39***	0.38***	0.38***
Past three months	(0.04)	(0.06)	(0.08)	(0.06)	(0.058)	(0.05)
Controls						
Net exports	No	No	No	No	No	Yes
Hurricane shut ins	Yes	Yes	No	No	Yes	Yes
*Crude oil price**	Yes	Yes	No	No	Yes	Yes
** included in both equations*						
Observations	120	120	120	120	120	120
Time Trend I	3	3	3	2	3	3
R-squared Supply	0.38	-0.74	-0.74	-0.91	0.12	0.27
R-squared Demand	0.96	0.95	0.95	0.94	0.95	0.96

Notes: The dependent variable is the total monthly quantity of natural gas delivered to consumers. For **demand** coefficients on futures price are estimates of 3-month demand elasticity. For **supply** coefficients on Henry Hub Price are estimates of supply elasticity. Columns (1)-(6) vary by the estimation method, types of controls and the order of the polynomial time trend included. All columns except (4) include a 3rd order polynomial time trend. Column (1) presents the OLS estimates with no IVs. All columns include a control on the RHS for the quantity of gas in storage. Controlling for storage levels increases the strength of the correlation between current month weather, HDD and CDD and Henry Hub price. Monthly data covers the time span from January 2001 through December 2010. Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9 Demand and Supply by Futures Price and Instrument Type

This table is most directly comparable to column (6) in Table 2 in the *Results*

	Model			
	3SLS	**3SLS**	**3SLS**	**3SLS**
VARIABLES	(1) Quantity Demanded	(2) Quantity Demanded	(3) Quantity Demanded	(4) Quantity Demanded
Instrument with gross storage shocks				
Ln(Futures_1mo)	-0.18***			
E[p_t | $_{t-1}$]	(0.038)			
Ln(Futures_2mo)		-0.145***		
E[p_t | $_{t-2}$]		(0.03)		
Ln(Futures_3mo)			-0.12***	
E[p_t | $_{t-3}$]			(0.026)	
Ln(Futures_4mo)				-0.12***
E[p_t | $_{t-4}$]				(0.025)
Elasticity of Supply	0.940***	0.938***	0.938***	0.942***
p_t	(0.11)	(0.11)	(0.11)	(0.11)
Instrument with weather-induced storage shocks				
Ln(Futures_1mo)	-0.205***			
E[p_t | $_{t-1}$]	(0.058)			
Ln(Futures_2mo)		-0.195***		
E[p_t | $_{t-2}$]		(0.056)		
Ln(Futures_3mo)			-0.21***	
E[p_t | $_{t-3}$]			(0.068)	
Ln(Futures_4mo)				-0.21***
E[p_t | $_{t-4}$]				(0.06)
Elasticity of Supply	1.03***	1.03***	1.02***	1.03***
p_t	(0.13)	(0.13)	(0.13)	(0.13)
Hurricane shut ins	Yes	Yes	Yes	Yes
*Crude oil price**	Yes	Yes	Yes	Yes
** included in both equations*				
Observations	120	120	120	120
Time Trend I	3	3	3	3
R-squared				

Notes: The dependent variable for both the supply and demand equations is the total monthly quantity of natural gas delivered to consumers. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 10 Demand with 1, 2, 3 and 4-month NYMEX futures prices by Consumer Type

This table is most directly comparable to Table 3 in the *Results*

	Model				
	3SLS	**3SLS**	**3SLS**	**3SLS**	**3SLS**
VARIABLES	(1) Commercial Quantity Demanded	(2) Residential Quantity Demanded	(3) Industrial Quantity Demanded	(4) Electricity Quantity Demanded	(5) Vehicle Quantity Demanded
	Instrument with gross storage shocks				
Ln(Futures_1mo)	-0.25***	-0.43***	-0.16***	-0.22***	0.056
E[p_t | $_{t-1}$]	(0.05)	(0.08)	(0.035)	(0.056)	(0.04)
Ln(Futures_2mo)	-0.20***	-0.34***	-0.12***	-0.19***	0.04
E[p_t | $_{t-2}$]	(0.04)	(0.06)	(0.027)	(0.047)	(0.03)
Ln(Futures_3mo)	-0.18***	-0.31***	-0.10***	-0.15***	0.05**
E[p_t | $_{t-3}$]	(0.038)	(0.05)	(0.02)	(0.04)	(0.026)
Ln(Futures_4mo)	-0.17***	-0.30***	-0.087***	-0.13***	0.05**
E[p_t | $_{t-4}$]	(0.036)	(0.05)	(0.02)	(0.03)	(0.025)
Elasticity of Supply	0.94***	0.94***	0.93***	0.94***	0.94***
p_t	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
	Instrument with weather-induced storage shocks				
Ln(Futures_1mo)	-0.24***	-0.35***	-0.25***	-0.25***	-0.016
E[p_t | $_{t-1}$]	(0.077)	(0.11)	(0.068)	(0.08)	(0.05)
Ln(Futures_2mo)	-0.23***	-0.30***	-0.24***	-0.28***	-0.04
E[p_t | $_{t-2}$]	(0.07)	(0.097)	(0.06)	(0.09)	(0.06)
Ln(Futures_3mo)	-0.27***	-0.34***	-0.25***	-0.28***	-0.02
E[p_t | $_{t-3}$]	(0.08)	(0.11)	(0.07)	(0.10)	(0.06)
Ln(Futures_4mo)	-0.27***	-0.36***	-0.23***	-0.24***	0.004
E[p_t | $_{t-4}$]	(0.08)	(0.11)	(0.07)	(0.09)	(0.05)
Elasticity of Supply	1.03***	1.03***	1.01***	1.02***	1.00***
p_t	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Observations	120	120	120	120	120
Time Trend I	3	3	3	3	3

Notes: The dependent variable for both the supply and demand equations is the total monthly quantity of natural gas delivered to consumers. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Chapter 2

DRILLING AND EXPLORATION

Introduction

The development of hydraulic fracturing and horizontal drilling technologies has resulted in an abundance of natural gas in the United States. This positive supply shock has increased adoption of natural gas as a source of energy and raised interest in the ability to predict future supply and production levels. Accurate estimates of drilling and exploration elasticities could ultimately be used to help predict how supply will evolve over the intermediate future. This paper uses exogenous weather-driven variation in price, within both a simultaneous equation and a single IV equation framework, to generate empirical estimates of the price elasticity of drilling and exploration.

Numerous academic studies have examined the responsiveness of natural gas drilling and reserves to price. A common assertion in this work is that demand is more volatile than supply. In particular, it is assumed that income and population growth, increasing electricity generation and gas heating have tended to shift demand out over time. Empirical studies have argued, therefore, that market equilibrium quantities and prices approximately trace out a supply curve [Fisher (1964); Erickson and Spann (1971); Pindyck (1974); Erickson; Millsaps and Spann (1974); Eyssell (1978); Deacon et al. (1983); Griffin and Moroney (1985)]. Working under this assumption most studies have sidestepped the issue of potential price endogeneity when estimating elasticities of drilling and exploration activities. While this has been expedient it may not be appropriate, especially in recent years. Significant technology-related supply shocks, including the development of hydraulic fracturing and horizontal drilling, make the assumption that shifts in demand are larger and more frequent than shifts in supply difficult to justify.

While price increases do affect drilling, they also augment production which pushes price back down. This reverse causality creates a circumstance whereby the effect of price on drilling and exploration is no longer well defined. Supply shocks can also have a direct effect on drilling (e.g. fracking technology) as well as an indirect effect on drilling and exploration through their effect on price. For these reasons, price endogeneity should be explicitly addressed in the models. Additionally, demand and drilling equations may be correlated with each other through their disturbance terms. This suggests that simultaneous equations may be more efficient than single IV equation estimation. Similar to the issue of price endogeneity, correlation in the error term has generally not been addressed in previous work; instead, drilling and exploration elasticities have been estimated in single equations.

This paper utilizes exogenous instruments for price within a simultaneous equation framework in order to explicitly account for the endogeneity of price and the correlation of demand and drilling and exploration equations through their error terms. Comparing instrumented estimates to OLS provides a test of the validity of the exogenous price assumption in previous work. I find evidence that price is, in fact, endogenous and propose a more robust method for generating drilling and exploration elasticities in the current industry environment.

Specifically, this model uses weather-related price shocks to identify the elasticity of drilling and exploration over time. The dependent variables are measures of drilling and exploration activity each month for ten consecutive months in the future. This allows me to compare the effects of price on drilling and exploration activity in each month up to ten months after a price shock. Current month weather shocks are the instruments for price in the drilling equation. Given enough time, producers can respond to spot price movements by drilling more or fewer wells. In the simultaneous equation framework weather-induced storage shocks are used to identify short-run demand. Storage shocks constitute a shift in supply and therefore identify the short-run demand curve. In the single IV equation, weather-induced storage shocks are used as instruments in the drilling equation. This is because, in the long run, producers can also respond to price movements caused by storage shocks.

In Chapter 1 a similar simultaneous equation framework is applied to estimate short-run supply and demand in U.S. natural gas. The main difference between that paper and this one is that production is less constrained in the intermediate term since firms have time to invest capital and augment production capacity with additional drilling and exploration. Supply in the short-run is constrained by the number of currently producing wells and inventory levels in storage. Suppliers can only respond to price changes in the short-run by augmenting sales with withdrawals from underground storage or by reinserting gas into storage to sell later.

In the intermediate future, however, producers affect production and storage levels by choosing whether or not to conduct seismic exploration activities and drill new wells. Since production from existing wells declines over time, producer decisions to replace existing wells with more or fewer wells in the future, have strong implications for supply in the intermediate future. It has been demonstrated that without new wells the production path follows an exponential decline curve (McCray 1975). In recent years, the time scale over which producer drilling decisions affect supply has shortened as the number of shale and other "tight gas" wells has increased; these wells often have very high initial production rates that drop off more rapidly than traditional wells. Consequently, producer drilling decisions affect the domestic supply more quickly than in the past. This paper attempts to provide further insight to the drilling and exploration process by assessing the level of drilling activity month to month after a price shock. This differs from all previous studies in the literature which have estimated drilling elasticities on a yearly time scale.

Review of the Literature

Many studies in the literature have estimated the elasticity of drilling and exploration in oil and gas. As previously stated, these models have not explicitly addressed the endogeneity of price. Studies of oil and gas economics acknowledge that they have so far done a poor job predicting how production capacity and reserves respond to price. Conversely, they often tout their ability to estimate drilling elasticities. Fisher (1964) develops a method for estimating the elasticity of oil reserves that has become the basis of most long-run oil and natural gas studies. He finds the reserve elasticity of oil to be between 0.31 and 0.82. He does not estimate an elasticity of natural gas. His basic method has been used in most studies estimating the reserve, production capacity, and drilling elasticities of oil and gas over the last fifty years.

Dahl and Duggan (1998) formalize and expand Fisher's intuitive economic method in an attempt to give it a theoretical framework. They reposition the estimation method within the framework of a firm objective function. Producers maximize the net present value of profit based on the expected return on investment of drilling and exploration. Production is a function of exploration activity, the number of wells drilled, the nature of the geology in the areas drilled and, as always, the random nature of gas discovery. The production function of oil or gas is represented by the function F(E, W, N, ε, R) where E are exploration inputs (e.g. seismic geological surveys), W are the number of wells drilled, N are characteristics of the geology being explored, R is the quantity of known reserves and ε captures the inherent randomness of discovery. Solving the firm profit maximization equation they show that the gas drilling equation is a function of the cost of drilling[9], the expected value of gas prices, the price of oil, taxes and interest rates over the production horizon and the geology of the area. They assert that economic theory necessitates the inclusion of all these variables in an OLS estimation equation. In a survey of the petroleum literature they then concluded that all major studies to date had failed to include variables suggested by economic theory and therefore suffered from omitted variable bias.

Two early studies, using a dataset similar to Fisher, estimate the elasticity of wildcat drilling and drilling into known reserves separately [Erickson (1968); Erickson and Spann (1971)]. These studies divide the drilling into two different dependent variables; namely, wildcat wells, which are the riskier and more explorative type of drilling and developmental wells, which involve drilling into reserves with proved production potential. Their improvement over Fisher's model is to account for the fact that wildcat wells and developmental wells are investments with different potential risks and benefits. This more flexible model allows each type of drilling to have a different elasticity with respect to price.

Kolb (1978) finds that drilling in proven reserves, an activity with a much higher probability of success is more sensitive to price. Several other studies estimate similar models with different datasets and include additional cost and interest rate variables [MacAvoy and Pindyck (1973); Pindyck (1974); and Pindyck

[9] Includes royalty, permit and other lifting costs

(1978); Walls (1994)]. Kolb (1979) presents the first attempt to estimate separate reserve elasticities of oil and gas following natural gas deregulation. He estimates the reserve elasticity of oil at 0.9 and natural gas at 0.84, both statistically significant. A more recent study uses a weighted average of oil and gas prices in order to estimate a single elasticity of petroleum reserves on U.S. aggregate data from 1960-1990; it finds drilling price elasticity to be 0.48 and significant [Al Shami (1995)]. Dahl and Duggan (1998) note in their survey that several studies use U.S. aggregate data and as a result, geological differences across regions do not appear to influence the estimations [Al Shami (1995); Porter (1992); Walls (1991)]. They conclude that models using aggregate data may be able to exclude geological variables in the estimation. A few studies examine the elasticity of drilling at the firm level [Ghouri (1991); Lledare et al. (1995)].

The estimates of natural gas drilling elasticities in the literature are varied and generally have much smaller magnitude than the estimates generated in this work. Wilkinson (1983) finds U.S. aggregate drilling elasticity to be 0.15 and statistically significant. Erickson and Spann (1971) find aggregate drilling elasticity to be 0.35 and Al Shami (1995) finds it to be 0.48, both are statistically significant. Many other studies find that gas drilling is not significantly correlated with price [Khazzoom (1971); MacAvoy and Pindyck (1973); Pindyck (1974)]. The study most similar in method to this one is Krichene (2002), which uses simultaneous equations to estimate drilling and demand on a data series ending in 1999. In nearly all specifications this study finds negative drilling elasticities. Weather variables were not included in either of this paper's simultaneous equations, however. A few studies find larger natural gas drilling elasticities, more similar to those found in this work. Epple (1975) finds drilling elasticity to be 0.74 and statistically significant. Lledare (1995) finds drilling elasticity in West Virginia to be 1.02 using individual firm data. In all of these studies, with the exception of Krichene (2002), the exogeneity of price is assumed, and variables suggested by economic theory are omitted.

Empirical Model

The simultaneous equations used to estimate drilling and exploration elasticity are the following:

$$\text{Drilling and Exploration:} \quad ln(x_{t+i}) = a_s + \beta_s\, ln(p_t) + \delta\sum_{i=1}^{3} stor_{t-i} + \delta r_t + f(t) + u_t \qquad (1)$$

$$\text{Demand:} \quad ln(q_t) = a_d + \beta_d\, ln(p_t) + \gamma_d w_t + g(t) + v_t \qquad (2)$$

The dependent variable in the drilling equation, x_{t+i}, is any of three measures of drilling and exploration activity i months after a price shock. These include the number of active rotary rigs, the number of developmental wells, and number of exploratory wells. p_t is the wellhead price or Henry Hub spot price. The relevant price from the perspective of the producers depends on the extent of each firm's vertical integration. Small producers may sell their gas at the wellhead while integrated firms retain possession all the way to the spot market. Elasticities are measured and compared using both price measures. β_s is the elasticity of drilling or exploration estimated by the model. $\delta\sum_{i=1}^{3} stor_{t-i}$ is the sum of weather-induced storage shocks in the previous three months. In the simultaneous equation framework weather-induced storage shocks are included in the supply equation only and therefore, become the instrument for price in the demand equation. r_t represents the controls including the annual average cost per foot of drilling and the spot price of Cushing crude oil. The price of oil is included since many energy companies produce both natural gas and oil and must allocate limited capital between these two ventures. Cost of drilling is included for obvious reasons. *f(t)* is a polynomial or fixed effects yearly time trend. Controlling for levels of drilling activity at yearly intervals is important because technological advances from 2000 to 2010 created significant increases in drilling and exploration activity. Lastly, u_t is the random *i.i.d.* error term.

The dependent variable in the demand equation q_t is the quantity of natural gas actually delivered down pipeline to a buyer. w_t is weather and includes four separate measures; the observed HDD and CDD per month and the deviation of HDD and CDD from the 30-year climate normal. Hereafter, the deviations in HDD and CDD from month-specific climate normals are simply referred to as weather shocks. Weather shocks are excluded from the supply equation and become the instruments for price that identify drilling elasticity. *g(t)* is a polynomial or fixed effects yearly time trend controlling unobserved shifts in demand due to macroeconomic factors and v_t is the error term.

The demand elasticities are not a focus of this study and the parameter estimates are not examined in any depth. There is evidence, however, that this estimation framework produces good estimates of short run demand elasticities.

The work on this topic in Chapter 1 demonstrates that this framework is limited and only appropriate for forecasting demand responses one to three or four months after a price shock. The reason the simultaneous equation framework is preserved and demand is included in this study, is to account for the fact that drilling and demand may be correlated through their error terms u_t and v_t.

This error correlation is likely if demand for natural gas shifts out as potential consumers become aware of significant increases in domestic supply. These demand shifts are unobserved by the econometrician and could influence producer decisions to explore and drill new wells. Estimating drilling elasticities without accounting for these unobserved correlated demand shocks, as in single IV equation estimation, could be inefficient or even cause the model to overestimate the parameters. From this perspective, it is preferable to estimate drilling and exploration elasticities within a simultaneous equation framework that includes demand. The preferred estimates in this study are therefore those assembled from the simultaneous equations. For comparison purposes the elasticity of drilling using a single IV equation is also estimated.

Assumptions and the Identification Strategy

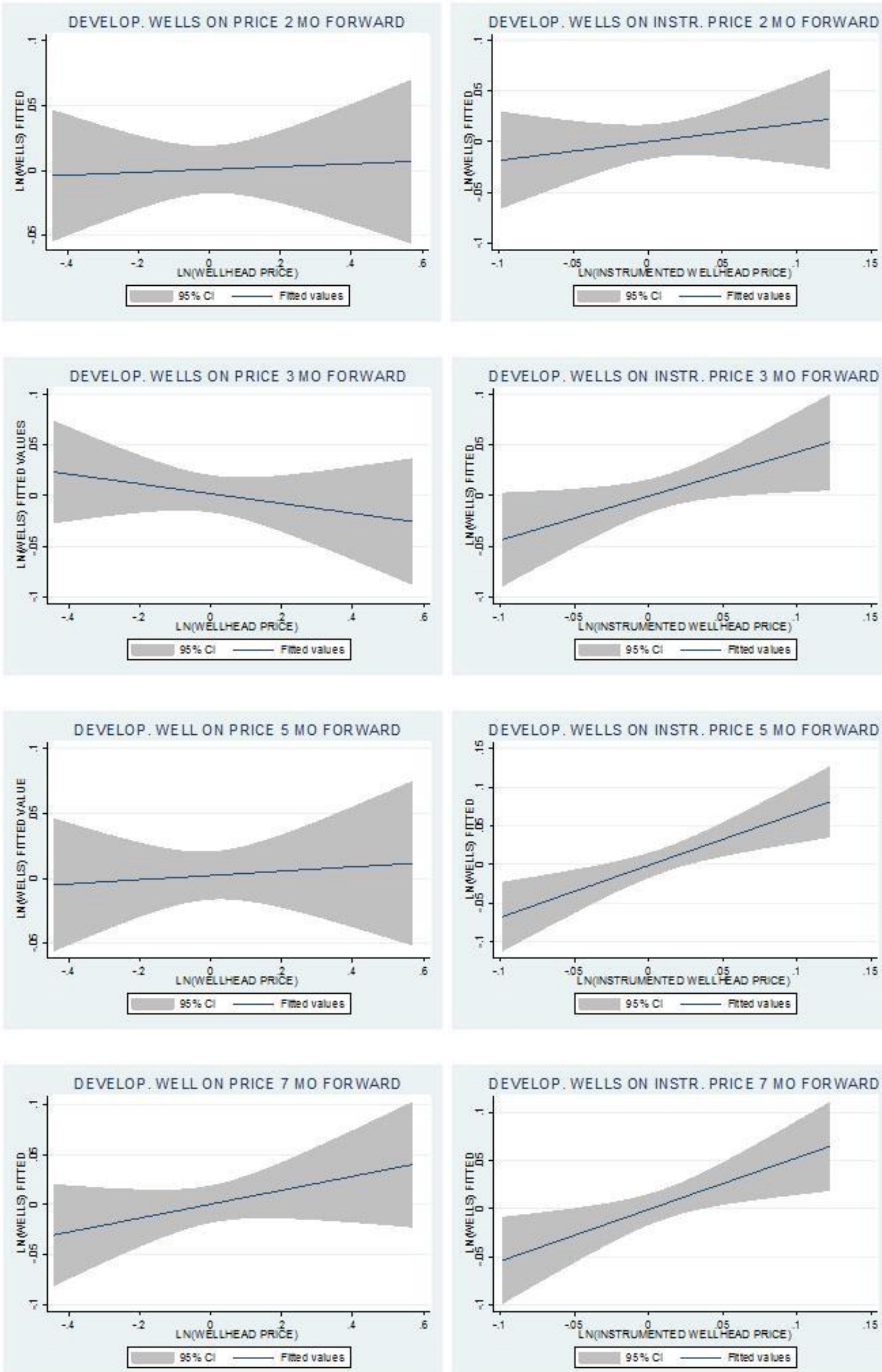
Each identification strategy rests on two main assumptions. The first, in the simultaneous equation framework, is that weather shocks are a valid instrument for price. In order to estimate an unbiased, consistent elasticity of drilling β_s the instrumental variables must isolate exogenous variation in price and be otherwise unrelated to drilling and exploration activity. In this respect weather shocks appear to be an ideal instrument. It is well established that they shift demand and raise price in spot markets [Mayer (1977); Mu (2007)]. Furthermore, they cannot be anticipated by producers before drilling and exploration decisions are made thereby satisfying the exclusion restriction. The first assumption in the single IV equation is similar; namely, that consecutive, compounding weather-related price shocks in the previous three months are a valid instrument for price in the drilling equation.

The second assumption is that movements in price in the current month, caused by either weather or weather-induced storage shocks, affect drilling and exploration behavior in future months. This assumption is less straightforward than the first. It is important to understand that producers have to obtain leases, permits, mineral rights and allocate capital in order to conduct drilling and exploration activity. These processes take time and effort. For profit maximizing firms, this means decisions must be based on expected price. I spell out two mechanisms by which current price shocks could plausibly affect producers' expectations of future prices.

First, producers may base their expectation of future price on current price and a random component. In other words, they may view price as a random walk. Positive price shocks today, especially large price shocks, thus increase the expected future price and increase future drilling activity. This is plausible given that oil prices have been shown to behave as a random walk (Walls 1994). Alternatively, producers may not view price as a random walk but instead monitor storage levels as an indicator of supply and future price. Take the following example. When consecutive compounding weather shocks occur, generating high demand, then spot prices go up. Also storage levels decrease. Producers, observing depletion in storage, anticipate that prices will remain elevated until storage quantities are returned to prior levels.

Whether or not the reader finds these mechanisms of price-to-expected-price transference plausible, there is descriptive evidence that drilling responds to weather-related price shocks. Figure 1 below displays a series of linear fit plots in order to highlight the relationship between drilling activity and weather-related price shocks. On the left side are four fit plots of the number of wells drilled on wellhead price. The dependent variables are the number of wells drilled 2, 3, 5 and 7 months forward of the observed wellhead price. Both variables are transformed with natural logs and detrended with year fixed effects. This is achieved by regressing each of the dependent variables on year fixed effects and plotting the residuals on wellhead price. A linear function with 95% confidence intervals is then fit on the plot of developmental wells on price. The same process is applied to fit plots on the right side, only this time, the instrumented value of wellhead price is used instead of actual wellhead price. Instrumented wellhead price is constructed by regressing log price on current weather shocks and sum of lagged weather-induced storage shocks, as in a first stage regression. The number of wells drilled is then plotted on the predicted values for price. The predicted values for price now represent exogenous, weather-related movements in price.

Figure 1



Notes: Linear plots fit the natural log of the number of developmental wells drilled on wellhead price a indicated number of months following a price change. Shaded regions represent the 95% confidence intervals. On the left side the natural log of observed price is used. On the right side the fitted values of price from a regression on the IVs is used. IVs include weather shocks and weather-induced storage shocks.

Plotting wells drilled on exogenous movements in price removes bias and the plots subsequently display a stronger visual correlation between the two variables.

Comparing plots on the right and left side there are several key differences. First, while there is generally a positive relationship between price and the number of wells drilled on both sides, the upward trend is steeper for weather-related price movements. This indicates that the relationship between price and drilling activity is stronger when considering only weather-related variation in price. Additionally, the confidence intervals for predicted wells are smaller when fit on weather-related movements in price. This indicates that instrumented price is likely a better predictor of drilling activity than uninstrumented price. Differences in both the slope and precision of the linear plots highlight the potential endogeneity of price in plots on the left hand side. They also suggest the potential usefulness of weather as an instrument. The relationship between price and wells drilled is generally flatter and less precise in more recent months regardless of which price is used. This further suggests that, in either case, price will be a better predictor of drilling activity many months after a movement in price rather than immediately after. This trend is confirmed with estimates in the empirical model.

Data

Data for the U.S. production, consumption, storage and price series of natural gas are from the U.S. Energy Information Administration (EIA) Natural Gas database. Dependent variables are the number of rotary rigs in operation, the number of developmental wells and the number of exploratory wells. Rotary rigs are mobile drilling equipment. The number of rigs in operation is a good leading indicator of drilling activity. Developmental wells are drilled into reservoirs proven to produce gas and are less risky than exploratory wells. Exploratory wells are drilled into reservoirs at depths where geological evidence has indicated, but not proven, the possibility of gas or where it is believed production from a formerly producing reservoir can be augmented. The price series used are monthly wellhead price and monthly Henry Hub spot price. Controls are the annual average cost per foot of drilling gas wells and the price of Cushing crude oil which is found in the Petroleum & Other Liquids database. All data series, except cost, are monthly.

U.S. weather data are from the National Oceanic and Atmospheric Administration NOAA. Variables are the U.S. monthly HDD and CDD along with the climate normals; the thirty year month-specific averages. Values are weighted by population in order to better predict total energy use.

Instruments are constructed from the weather and storage variables. Weather shocks are calculated as the observed deviations in HDD and CDD from the monthly climate normal. Weather shocks are summed over the previous three months in order to characterize weather shocks as successive, compounding shocks. Similarly, storage shocks are calculated as the observed deviations from thirty year month-specific averages. Fitted values from a regression of storage shocks on weather shocks are then used to represent weather-induced storage shocks.

Results

In order to demonstrate that weather shocks satisfy the relevancy restriction as instruments for both Henry Hub and wellhead price the first stage results are presented in tables 1 and 2.

Table 1.

FIRST STAGE: LN(WELLHEAD PRICE)	
HDD Weather Shock	0.06***
100 HDD w_t	(0.01)
CDD Weather Shock	0.04**
100 CDD w_t	(0.01)
LN(Crude Price)	0.46***
	(0.16)
Drilling Cost	0.4
Per foot($1000)	(0.5)
3 Month Storage Shock	-0.0241***
Weather-induced (100MMcf)	(0.006)
Observations	84
Time Trend I	3
F STAT = 33.34	

Table 2.

FIRST STAGE: LN(HENRY HUB PRICE)	
HDD Weather Shock	0.12***
100 HDD w_t	(0.02)
CDD Weather Shock	0.25***
100 CDD w_t	(0.05)
LN(Crude Price)	0.71***
	(0.19)
Drilling Cost	0.2
Per foot($1000)	(0.7)
3 Month Storage Shock	-0.262***
Weather-induced (100MMcf)	(0.007)
Observations	84
Time Trend I	3
F STAT = 25.74	

Next, unit root tests are performed to see whether either price series is a random walk. To restate, the assumption is that random-walk-like persistence of price shocks into the future is one potential mechanism by which current price could influence producers' future drilling decisions. The Augmented Dickey-Fuller-GLS test for a unit root with Eliot, Rothenberg and Stock (1996) critical values is used to test for the presence of a unit root. The ADF test fails to reject the null hypothesis of a unit root for both the Henry Hub and wellhead price series at the 10% level. This implies that price shocks, to some extent, persist through time and provides partial evidence that weather-related price shocks in the current month may shape producers expectation of future price. The ADF test statistics and critical values are displayed in tables 3 and 4 below.

Table 3. DF-GLS UNIT ROOT TEST

VARIABLE		Critical Value		
Ln(Well Head Price)				
Lags	*DF-GLS tau Test Statistic*	1%	5%	10%
17	-0.892	-3.480	-2.819	-2.536
16	-0.984	-3.480	-2.823	-2.541
15	-1.073	-3.480	-2.828	-2.545
14	-1.159	-3.480	-2.833	-2.549
13	-1.185	-3.480	-2.837	-2.553
12	-1.272	-3.480	-2.841	-2.557
11	-1.337	-3.480	-2.846	-2.561
10	-1.121	-3.480	-2.850	-2.565
9	-1.035	-3.480	-2.854	-2.569
8	-1.145	-3.480	-2.858	-2.572
7	-1.463	-3.480	-2.862	-2.576
6	-1.422	-3.480	-2.866	-2.579
5	-1.370	-3.480	-2.869	-2.582
4	-1.239	-3.480	-2.873	-2.586
3	-1.371	-3.480	-2.876	-2.589
2	-1.344	-3.480	-2.880	-2.592
1	-1.778	-3.480	-2.883	-2.595

Table 4. DF-GLS UNIT ROOT TEST

VARIABLE		Critical Value		
Ln(Henry Hub Price)				
Lags	*DF-GLS tau Test Statistic*	1%	5%	10%
13	-1.534	-3.478	-2.806	-2.529
12	-1.690	-3.478	-2.820	-2.542
11	-1.797	-3.478	-2.834	-2.555
10	-1.739	-3.478	-2.847	-2.567
9	-1.718	-3.478	-2.860	-2.579
8	-2.199	-3.478	-2.873	-2.590
7	-2.415	-3.478	-2.885	-2.601
6	-2.403	-3.478	-2.896	-2.612
5	-2.205	-3.478	-2.907	-2.622
4	-2.399	-3.478	-2.918	-2.631
3	-2.076	-3.478	-2.927	-2.640
2	-2.038	-3.478	-2.936	-2.648
1	-1.923	-3.478	-2.945	-2.656

Table 5 shows results from the simultaneous equation model using Henry Hub spot price. Displayed are results for each of the dependent variables from one to ten months following a weather-related price shock. Column (1) displays the elasticity of drilling exploratory, wildcat wells, column (2) displays the elasticity of developmental wells and column (3) displays the elasticity of active rotary rig counts. In the column to the right of each estimate is the r-squared value and chi-square for each drilling equation. All models include controls for the average cost per foot of drilling, the natural log of oil price and a polynomial time trend. Coefficients should be interpreted as the percent change in drilling and exploration activity t months after a price shock. The counterfactual is the drilling and exploration activity in the month preceding the price shock. There is a statistically significant uptick in the number of active rotary rigs two to three months after a price shock, a significant increase in developmental wells four months afterwards and a significant increase in exploratory wells five months afterwards. Each of these effects persists up to eight months after the initial price shock before declining or becoming statistically insignificant.

The maximum elasticity of developmental wells is 0.6, implying that a 10% increase in the Henry Hub price results in a 6% increase in drilling within seven to eight months of a price shock. Notably, this estimate is larger and has smaller standard errors than what has most often been found in previous work when no instrument is used for price. Also, the elasticity is approximately the same for exploratory drilling as it is for developmental drilling, although on a one month lag.

Table 6 displays results when the model uses wellhead price on the RHS. The columns and control variables are the same as before. The maximum elasticity for exploratory drilling is 1.0 and for developmental drilling is 1.24. A 10% increase in wellhead price is now correlated with a 10% increase in exploratory drilling and a 12.4% increase in developmental drilling within 7 months of a price shock.

The relative timing across the dependent variables is consistent and intuitive. Rotary rig activity, moving to location and drilling, precedes the completion of a well. Exploratory wells are higher risk and more likely to require additional planning or preparation than developmental wells.

Table 5 Drilling and Exploration Activity After a Henry Hub Price Shock

	3SLS		3SLS		3SLS	
VARIABLES	Ln(Explor. Well)	R-sq	Ln(Develop. Well)	R-sq	Ln(Rotary Rigs)	R-sq
Ln(Henry Hub Price)	(1)	(chi2)	(2)	(chi2)	(3)	(chi2)
1 month forward	-0.36**	0.86	-0.22**	0.79	0.01	0.90
	(0.16)	(565.2)	(0.09)	(322.6)	(0.07)	(820.8)
2 months forward	-0.21	0.86	-0.10	0.79	0.10	0.91
	(0.16)	(559.9)	(0.09)	(325.9)	(0.06)	(921.9)
3 months forward	-0.013	0.87	0.01	0.81	0.21***	0.92
	(0.16)	(567.4)	(0.09)	(358.2)	(0.06)	(1055.3)
4 months forward	0.05	0.87	0.26***	0.85	0.32***	0.93
	(0.16)	(559.9)	(0.08)	(467.2)	(0.06)	(1190.7)
5 months forward	0.39***	0.89	0.49***	0.86	0.37***	0.93
	(0.14)	(677.3)	(0.07)	(563.1)	(0.06)	(1216.0)
6 months forward	0.48***	0.88	0.61***	0.81	0.37***	0.94
	(0.15)	(618.8)	(0.09)	(417.3)	(0.05)	(1318.4)
7 months forward	0.59***	0.87	0.61***	0.79	0.31***	0.94
	(0.16)	(567.7)	(0.09)	(371.7)	(0.05)	(1398.6)
8 months forward	0.66***	0.84	0.54***	0.76	0.22***	0.94
	(0.17)	(482.7)	(0.10)	(308.8)	(0.05)	(1506.6)
9 months forward	0.49***	0.86	0.30***	0.80	0.12**	0.95
	(0.16)	(520.5)	(0.09)	(362.5)	(0.05)	(1694.2)
10 months forward	0.27	0.85	0.03	0.83	-0.00006	0.95
	(0.16)	(493.2)	(0.09)	(427.7)	(0.05)	(1850.8)
Avg. Cost/Foot	Yes		Yes		Yes	
Ln(Crude oil price)	Yes		Yes		Yes	
Observations (min)	84		84		85	
Time Trend I	3		3		3	

*Estimates for elasticity of demand not shown

Each row presents the elasticity of drilling and exploration equation results of a unique simultaneous equation model *t* months following a weather-related price shock. The measure of price used is the U.S. average Henry Hub price of natural gas. Monthly data covers the time span from January 1, 2001 to December 31, 2007. Demand estimates not shown. Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table 6 Drilling and Exploration Activity after a Wellhead Price Shock

	3SLS		3SLS		3SLS	
VARIABLES	Ln(Explor. Well)	R-sq	Ln(Develop. Well)	R-sq	Ln(Rotary Rigs)	R-sq
Ln(Wellhead price)	(1)	(chi2)	(2)	(chi2)	(3)	(chi2)
1 month forward	-0.33**	0.87	-0.29***	0.77	-0.33	0.85
	(0.13)	(567.9)	(0.08)	(301.7)	(0.18)	(552.2)
2 months forward	-0.24	0.86	-0.14	0.78	-0.15	0.89
	(0.13)	(549.2)	(0.08)	(317.3)	(0.16)	(716.1)
3 months forward	0.03	0.87	0.02	0.80	0.08	0.92
	(0.13)	(575.1)	(0.07)	(346.2)	(0.13)	(1036.9)
4 months forward	-0.23	0.85	0.21	0.84	0.35***	0.93
	(0.35)	(503.8)	(0.17)	(458.3)	(0.08)	(1117.6)
5 months forward	0.44	0.87	0.81***	0.75	0.53***	0.91
	(0.32)	(597.2)	(0.22)	(294.5)	(0.14)	(979.3)
6 months forward	0.68**	0.88	1.16***	0.56	0.58***	0.91
	(0.31)	(638.2)	(0.29)	(174.31)	(0.14)	(924.2)
7 months forward	1.00***	0.83	1.24***	0.49	0.57***	0.91
	(0.37)	(460.7)	(0.32)	(149.5)	(0.14)	(944.6)
8 months forward	0.96***	0.84	1.17***	0.48	0.44***	0.93
	(0.36)	(487.9)	(0.33)	(142.6)	(0.13)	(1230.7)
9 months forward	0.49	0.88	0.69***	0.73	0.25**	0.95
	(0.30)	(663.1)	(0.23)	(268.2)	(0.11)	(1763.2)
10 months forward	0.34	0.86	0.18	0.83	0.03	0.95
	(0.33)	(549.7)	(0.19)	(426.5)	(0.10)	(1985.2)
Avg. Cost/Foot	Yes		Yes		Yes	
Ln(Crude oil price)	Yes		Yes		Yes	
Observations (min)	84		84		85	
Time Trend I	3		3		3	
*Estimates for elasticity of demand not shown						

Each row presents the elasticity of drilling and exploration equation results of a unique simultaneous equation model *t* months following a weather-related price shock. The measure of price used is the U.S. average wellhead price of natural gas. Exploratory wells are drilled in search of new gas reservoirs and carry the highest risk. Developmental wells are drilled into proven reservoirs and rotary rigs are the number of mobile drilling rigs active in the field. Monthly data covers the time span from January 1, 2001 to December 31, 2007. Demand estimates not shown. Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Additionally, ample anecdotal evidence exists to suggest that this time scale is reasonable for drilling.[10]

For robustness, the models were re-estimated with year fixed effects and compared with the results above. The magnitude of drilling and exploration elasticity estimates increase by about 0.10, or roughly one standard deviation, when yearly fixed effects are used instead of a polynomial time trend.

[10]From shalereporter.com, staking the well and planning out the pad boundaries takes one to two months. Drilling and completion takes approximately one month. Then the well must be stimulated and extraction can begin. In ideal circumstances, the entire process, from drilling to market place, takes as little as 3 or 4 months. Obtaining leases, permits and conducting geologic surveys can add substantially more time to the process, however.

Table 7 presents the OLS estimates of drilling elasticities for comparison with the 3SLS.

Table 7 Drilling and Exploration Activity OLS Parameter Estimates

	OLS	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**
VARIABLES *Ln(Price)*	(1) Ln(Exp. Well) *Henry Hub Price*	(2) Ln(Dev. Well) *Henry Hub Price*	(3) Ln(Rot. Rig) *Henry Hub Price*	(4) Ln(Exp. Well) *Wellhead Price*	(5) Ln(Dev. Well) *Wellhead Price*	(6) Ln(Rot. Rig) *Wellhead Price*
1 month forward	-0.27***	-0.14**	0.03	-0.24	-0.09	0.09**
	(0.08)	(0.05)	(0.03)	(0.11)	(0.07)	(0.04)
2 months forward	-0.13	-0.01	0.11***	-0.13	0.01	0.15***
	(0.08)	(0.05)	(0.03)	(0.11)	(0.11)	(0.04)
3 months forward	0.04	0.11***	0.16***	0.10	0.17***	0.20***
	(0.09)	(0.05)	(0.03)	(0.11)	(0.06)	(0.04)
4 months forward	0.15	0.21***	0.20***	0.27**	0.23***	0.22***
	(0.09)	(0.04)	(0.03)	(0.11)	(0.06)	(0.04)
5 months forward	0.33***	0.30***	0.22***	0.37***	0.33***	0.27***
	(0.09)	(0.04)	(0.03)	(0.12)	(0.05)	(0.04)
6 months forward	0.31***	0.32***	0.23***	0.45***	0.36***	0.28***
	(0.09)	(0.04)	(0.03)	(0.11)	(0.05)	(0.04)
7 months forward	0.33***	0.29***	0.20***	0.37***	0.34***	0.26***
	(0.09)	(0.04)	(0.03)	(0.11)	(0.05)	(0.04)
8 months forward	0.24***	0.21***	0.14***	0.35***	0.27***	0.21***
	(0.09)	(0.05)	(0.03)	(0.11)	(0.068)	(0.04)
9 months forward	0.26***	0.13**	0.09***	0.45***	0.22***	0.16***
	(0.09)	(0.05)	(0.03)	(0.11)	(0.07)	(0.04)
10 months forward	0.24**	0.04	0.04	0.43***	0.09	0.10***
	(0.10)	(0.05)	(0.03)	(0.12)	(0.07)	(0.03)
Avg. Cost/Foot	Yes	Yes	Yes	Yes	Yes	Yes
Ln(Crude oil price)	Yes	Yes	Yes	Yes	Yes	Yes
Observations (min)	84	84	84	84	84	84
Time Trend I	3	3	3	3	3	3

Each row presents the OLS estimate of elasticity of drilling and exploration equation results of a unique system of simultaneous equations *t* months following a price change. The measure of price used is the U.S. average wellhead price of natural gas. Monthly data covers the time span from January 1, 2001 to December 31, 2010. Demand estimates not shown. Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

The OLS model generates smaller but statistically significant estimates. The maximum elasticities for exploratory wells are 0.33 and 0.45, maximum elasticities for developmental wells are 0.32 and 0.36 and maximum elasticities for rotary rigs are 0.23 and 0.28. These are reasonably similar to OLS estimates of aggregate drilling by Wilkinson (1983), Erickson and Spann (1971), and Al Shami (1995), who found drilling elasticities of 0.15, 0.35, and 0.48 respectively.

Single Equation IV Estimation

While the simultaneous equations framework is ideal, a series of single equation instrumental variable regressions is also run to estimate elasticities. The single equation IVs are run with Newey-West standard errors to account for serial correlation. These can be compared with standard errors in the 3SLS, which do not use Newey-West standard errors, as a way to gauge the effect of autocorrelation. In the single IV equation, instrumental variables for price include both weather shocks and weather-related storage shocks. As the reader should remember, weather-related storage shocks are used to identify short-run demand in the simultaneous equations. This may at first appear contradictory. The overarching assumption is that weather-related storage shocks identify demand in the short-run when the number of existing wells and production are fixed. Beyond the short-run, however, storage shocks can be used to identify supply side parameters as well. With time to procure permits and allocate capital, producers can respond to weather-related storage shocks by increasing or postponing drilling activity.

The addition of this instrument to the first stage in the drilling equation has intuitive appeal. It explicitly incorporates the signaling process proposed in the second mechanism of price-shock-to-expected-price transference; namely, producers observe storage shocks and expect them to cause changes in price that persist into the future. Table 8 displays the single equation IV estimates.

Table 8 Drilling and Exploration Activity Single IV Equation Estimates

	SINGLE EQ IV	**SINGLE EQ IV**	**SINGLE EQ IV**	**SINGLE EQ IV**
	(1)	(2)	(3)	(4)
VARIABLES	Ln(Explor. Well)	Ln(Develop. Well)	Ln(Explor. Well)	Ln(Develop. Well)
Ln(Henry Hub Price)	*Henry Hub Price*	*Henry Hub Price*	*Wellhead Price*	*Wellhead Price*
1 month forward	0.03	-0.40*	0.46**	-0.11
	(0.28)	(0.21)	(0.21)	(0.19)
2 months forward	0.017	-0.37*	0.36	-0.26
	(0.26)	(0.20)	(0.19)	(0.20)
3 months forward	-0.17	-0.24	0.18	-0.38
	(0.28)	(0.19)	(0.21)	(0.22)
4 months forward	-0.15	0.11	0.16	-0.24
	(0.27)	(0.14)	(0.19)	(0.19)
5 months forward	0.09	0.53***	0.31	0.09
	(0.26)	(0.16)	(0.19)	(0.18)
6 months forward	0.53**	0.82***	0.65***	0.45***
	(0.23)	(0.22)	(0.19)	(0.16)
7 months forward	0.96***	1.01***	0.99***	0.75***
	(0.32)	(0.29)	(0.23)	(0.17)
8 months forward	1.33***	0.96***	1.25***	0.86***
	(0.43)	(0.28)	(0.26)	(0.18)
9 months forward	1.18***	0.62***	1.12***	0.78***
	(0.41)	(0.22)	(0.23)	(0.17)
10 months forward	0.81***	0.09	0.95***	0.43***
	(0.30)	(0.16)	(0.20)	(0.17)
Avg. Cost/Foot	Yes	Yes	Yes	Yes
Ln(Crude oil price)	Yes	Yes	Yes	Yes
Observations (min)	96	96	96	96
Time Trend I	Yearly f.e.	Yearly f.e.	Yearly f.e.	Yearly f.e.

Parameter estimates are generally not meaningfully different from those in the simultaneous equations model. Elasticities in columns (1) – (3) are larger in magnitude in the single equation IV regressions. This could be because, outside of the simultaneous equation framework, unobserved shifts in demand now create positive bias in the estimates. This may provide evidence that the errors terms are correlated across equations. This adds some justification for the designation of estimates from the simultaneous equations model as the preferred estimates. The Newey-West standard errors, which account for serial correlation, are similar or slightly larger than previous standard errors.

Conclusion

This paper demonstrates how weather variables and a simultaneous equation model can be used to address price endogeneity when estimating drilling and exploration elasticities in U.S. natural gas. This framework is employed to estimate several elasticities drilling and exploration activity over time. The results illuminate important dynamic aspects of the drilling and exploration price response that characterized the natural gas industry from 2000 to 2010. Although numerous studies have quantified this relationship in the past, there are good reasons to re-estimate these elasticities. First, the industry has undergone significant structural changes within just the last decade due to continued deregulation and the abundance of shale gas; the sensitivity of drilling to price may have changed. Second, the endogeneity of price has generally not been addressed by previous models. The results in this study demonstrate, however, that estimates from models which do not explicitly address the endogeneity of price are likely to suffer significant downward bias. As consequence, previous estimation methods likely underestimate elasticities of drilling, at least in recent years.

Weather-related price shocks appear to drive increased drilling and exploration activity beginning three to five months after they occur. Drilling activity continues to increase up to eight months after the price shock. The models find the drilling elasticity for natural gas to be is close to, or exceeding 1.0 within seven months of a price shock. These estimates of drilling elasticity are higher than most in the literature, although, two other studies have estimated drilling elasticity as high as 0.74 and 1.02. It is important to note, however, when comparing these estimates to others that this paper estimates drilling elasticity month over month whereas all others measure drilling elasticity year over year.

A useful extension or addition to this paper would be to incorporate a model of gas discoveries. The traditional approach of multiplying drilling elasticities by well success rate and discovery per successful well have had very poor predictive powers. One possibility may be to combine the current model with an engineering model of well discovery in place of an econometric one. This could extend the estimation of drilling elasticities to calculate reserve elasticity.

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Chapter 3

THE EFFECT OF ENTRY ON AIRLINE PRICE DISPERSION

Introduction

This paper performs an event study to examine how legacy airline frequent flyer programs (FFP) combined with market power preserve an incumbents' ability to price discriminate despite increasing competition. A flexible model is employed in order to determine whether the effects of entry on incumbent fare dispersion are heterogeneous depending on incumbent capacity share at the origin airport. There is evidence that dominant capacity share at the origin airport preserves airlines' ability to price discriminate. The estimates demonstrate that a specific combination of incumbent, entrant, and market characteristics causes an incumbent's price dispersion to increase with competition. Additionally, an attempt is made to determine whether the ability to preserve price discrimination is not solely related to market power, but also facilitated through the use of FFP. This hypothesis is explored by examining how a dominant airline's ability to preserve price discrimination varies between long-haul and short-haul routes and between routes with large and small consumer preference heterogeneity.

The effect of competition on price dispersion has been the focus of several airline studies. A debate remains, however, whether competition increases or decreases price dispersion and whether the effect is monotonic. The “standard narrative” of price discrimination holds that as a firm loses market power, its ability to price discriminate diminishes and prices converge to marginal cost. It is appealing to test the standard narrative empirically with airlines since price dispersion can be considered a proxy for price discrimination and is observable in public data. Despite this appeal as low hanging research fruit, studies have confounded one another with contradictory findings regarding whether the standard narrative holds. Consequently, the argument has sustained interest for over a decade.

The first model estimated in this paper assumes that the effect of competition is homogeneous and monotonic. Entry of both a legacy (LGC) and a low cost carrier (LCC) on the same route in one quarter is found to reduce incumbent price dispersion by 6%. This is larger than the effect found for LGC entry alone which reduces price dispersion by 2%. LCC entry is estimated to increase price dispersion by 1.5%.

In the preferred specifications, effects of entry are allowed to vary by incumbent capacity share at the origin airport. Incumbents with less than 15%

capacity share at an airport are designated as "non-dominant" while those with greater than 25% are designated as "dominant". In this specification *both entry* is estimated to reduce price dispersion of a non-dominant incumbent by nearly 10%. The effect of *both* entry is four times smaller on incumbents with 15-25% capacity share and ten times smaller on dominant incumbents. These effects are small but heterogeneous and meaningfully different from each other.

There is descriptive evidence that the smaller effect of entry on a dominant airline's price dispersion may be due to that airline's FFP. This was found by examining the effect of competition on dominant airlines prices across route types for which the effectiveness of FFP would be expected to vary systematically. Specifically, the hypothesis formulated from the descriptive evidence, was that FFP should more effectively protect a dominant incumbent's price discrimination on long-haul rather than short-haul routes, and on routes with large consumer preference heterogeneity (high volumes of business *and* leisure travel) as compared to routes with low preference heterogeneity (predominantly leisure travel). The evidence which led to these hypotheses is provided in the body of the paper.

Support for these hypotheses becomes weak, however, when they are examined more rigorously in a panel data time series regression with carrier-route, and carrier-quarter fixed effects. Model results indicate that a dominant incumbent's price dispersion is more effectively protected on long-haul than short-haul routes as predicted but are estimated imprecisely. On routes between big cities, where greater preference heterogeneity is assumed, price dispersion actually decreases more with entry, except when the entrant is a low cost carrier. This occurs despite clear indications to the contrary in the descriptive statistics.

Unexpectedly, this study finds that incumbent price dispersion is decreasing six to nine months before entry actually occurs. Incumbent price dispersion is found to decrease prior to entry regardless of entrant type, LGC or LCC. This corroborates, to some extent, findings in other recent works [Goolsbee and Syverson (2008); Daraban and Fournier (2009); Huschelrath and Muller (2011)] that incumbent's average price decreases prior to entry in response to the threat of entry by Southwest. Dominant incumbents consistently begin pre-emptive fare reductions earlier than non-dominant incumbents. Since airlines with dominant status may have a larger vested interest in discouraging competition, this behavior could be interpreted as evidence of entry deterrence.

Review of the Literature

A seminal work on airlines by Borenstein and Rose (1994) and a study by Stavins (2001) both found that price dispersion increases with competition, contradicting the standard narrative of market power and price dispersion. They assert that FFP protect airlines from having to compete for high-value consumers. Instead, airlines compete by cutting prices to low-value consumers. As competition increases, price dispersion increases because there is proportionally greater downward pressure on the low end of air carriers' price distributions.

Alternatively, Gerardi and Shapiro (2009), find that price dispersion decreases with competition in a study using panel data. They show that the cross sectional empirical strategy used by Borenstein and Rose (1994) suffers from omitted variable bias that changes the signs of their coefficients. Gerardi and Shapiro (2009) have the weight of theory to back their findings but there are several reasons why there may still be concerns with their results as well. First, their identification relies heavily on the use of enplaned passengers on a route as an instrument for competition. It will be discussed below why this instrument may not be appropriate and how it likely causes them to overestimate the negative impact of competition on price dispersion.

Second, their empirical model imposes the assumption that the effects of competition are homogeneous and monotonic. Their model cannot determine if price dispersion increases with competition in some markets and decreases in others. Instead, it only identifies the dominant effect. This paper demonstrates why the assumption of homogeneous effects is unnecessarily strict and shows how a more flexible model illuminates a richer story.

Goolsbee and Syverson (2008) demonstrate that airlines respond to the threat of competition as well as actual market entry. In light of these findings, Gerardi and Shapiro (2009) may focus too narrowly on incumbent price responses in the time period in which market entry occurs. The model in this paper is expanded to observe how competition affects price dispersion up to three years before and a full year after entry in order to paint a more complete picture.

Another paper, Dai et al. (2010) estimates a more flexible model than Gerardi and Shapiro (2009) and finds a non-monotonic relationship between competitive intensity and airline price dispersion. As in Gerardi and Shapiro (2009), they use enplaned passengers on a route to instrument for competition and examine solely the period in which entry occurs. Dai et al. (2010) find price dispersion increases with competition in concentrated markets while price dispersion decreases with competition in competitive markets. They attribute this phenomenon to two opposing effects, the competitive effect and the incentive compatibility constraint. These findings are consistent with what we would expect to see if the combination of loyalty programs and large market share insulate price discrimination from competition, as will be explained below. This paper primarily tests the hypothesis that an airline's origin airport capacity share rather than market concentration, however, may drive the heterogeneous effects. In addition, focusing on airport capacity share has the added advantage of being able to test whether FFP are partially responsible for the heterogeneous effect of entry.

Contribution

This paper strives to improve upon and clarify the findings of the aforementioned studies. Works which concluded that the existence of FFP caused competition to increase price dispersion [Borenstein and Rose (1994) and Stavins (2001)] are based on estimates that have been shown to be biased. By using panel data and relaxing the assumption of homogeneous, monotonic effects, however, this paper is able to identify which firm and market characteristics induce price dispersion to increase, decrease or remain unchanged with competition.

A more difficult problem, encountered in all previous work on this topic, is the simultaneous determination of competition and incumbent price dispersion. Panel data cannot entirely untangle the endogeneity of airfares and market entry and the recent attempts to deal with this by instrumenting competition with enplaned passengers on a route [Gerardi and Shapiro (2009); Dai et al. (2010)] illicit some concerns. The main problem with using *enplaned passengers on a route* as an instrument is that this variable is likely embedded in the error term. This occurs because the assumption for using this instrument is that, changes in the number of enplaned passengers, are the result of idiosyncratic changes in demand for air travel. In order for *enplaned passengers* to be a good instrument for competition idiosyncratic shifts in demand for air travel across routes must be orthogonal to observed prices. Also, it is necessary for these demand shifts to be observable by the airlines and influence their entry and exit behavior. This could be the case if airports in growing cities or states experiencing increased demand for flights and the number of enplaned passengers from these airports increases on some routes more than others. Increased enplanements on these routes may then attract potential entrants and induce them to enter selectively into these markets.

While plausible, there is still good reason to be concerned that *enplaned passengers on a route* does not satisfy the exclusion restriction necessary to make it an appropriate instrument. Several studies find incumbents' average prices decreasing on routes where Southwest threatens to enter several quarters before entry actually occurs [Goolsbee and Syverson (2008); Huschelrath and Muller (2011)]. In addition, this study find that incumbents' price dispersions and premium fares are systematically decreasing more on routes that experience an entry than those that do not, two to four quarters before entry actually occurs. This trend is statistically significant in the case of both LCC and LGC entry. This is a problem for the instrument because systematic pre-emptive fare reductions themselves cause an increase in enplanements. In short, enplanements most likely increase on routes that ultimately experience entry because of incumbents' pre-emptive fare reductions, not due to an exogenous shift in demand. As a consequence, using *enplaned passengers on a route* as an instrument for entry will result in biased estimates.

The direction of the bias, at least, can be determined. Since enplanements on a route are negatively correlated with price dispersion, via pre-emptive fare reductions, but positively correlated with entry, then inclusion of the instrument and the exclusion of entry in the regression will result in negatively biased estimates. This is consistent with results in Gerardi and Shapiro (2009), as well as this paper, which both find unrealistically large, negative effects of entry on price dispersion when this instrument is used.

This work attempts to improve the identification strategy in the following ways. First, an event study model is constructed similar to Goolsbee and Syverson (2008). The specification includes a complete set of carrier-route and carrier-quarter fixed effects. This augments the slightly more parsimonious fixed effects models used by Gerardi and Shapiro (2009) and Dai et al. (2010) by controlling for carrier-quarter specific trends rather than just quarterly trends. The model estimates the effect of entry on incumbent airfares and price dispersion three years before and one full year after the quarter in which entry occurs. This necessitates the inclusion of dummy variables for a total of seventeen quarters (four years and three months) around each entry event. Additionally, the preferred specification includes enplaned passengers as an independent variable on the RHS.

For comparison, this paper estimates the model proposed by Gerardi and Shapiro (2009) with *enplaned passengers on a route* as well as another instrumental variable; *enplaned passengers at origin airport*. The latter instrument may constitute an improvement over the former one since changes in the number of airport-wide enplanements are more likely to capture changes in overall demand from economic conditions and less likely to be driven by consumer responses to systematic, pre-emptive fare reductions. Estimates using *enplaned passengers* as an instrument are compared to those without instruments and to the event study with fixed effects.

A final note, examining the possibility of a non-monotonic relationship between competition and price dispersion based on carrier's airport capacity share constitutes an important deviation from the study performed by Dai et al. (2010). By focusing on the initial level of market concentration and how it determines the effect of competition on price dispersion, Dai et al. (2010) end up averaging the effect across airlines on a route regardless of carrier-specific airport capacity share. The direction and magnitudes of their estimates may be misleading if dominant and non-dominant carriers' price dispersions respond differently to competition. Alternatively, their estimates may correctly estimate the effects of competition and the incentive compatibility constraint on price dispersion but lack the precision needed to clarify the role of a dominant carrier's FFP.

To see why, imagine a contrived example where two airlines operate on a route with starkly different capacity shares at the origin airport; United operates 70% of flights and capacity from Denver international airport while American Airlines operates 10%. Many carriers operate at DIA but assume only United and American offer flights from Denver to Chicago. Both respond to the entry of Southwest onto the Denver-Chicago route by cutting ticket prices. United is the dominant carrier, for flights originating from Denver, and its FFP offers more value to consumers here than either of its competitors' programs. Since high-value consumers consider both quality and price, United maintains an advantage over competitors when pricing to these consumers and makes proportionally larger cuts to low-end tickets. This increases price dispersion, contrary to the standard narrative.

Since American has low market share, its loyalty program does not have the same value advantage over Southwest as United. Consequently, it makes proportionally greater cuts to high-end tickets because price for these tickets is furthest above marginal cost. Consistent with the standard narrative, American's price dispersion decreases. To reiterate, the model used by Dai et al. (2010) averages these opposing effects on price dispersion. The direction and magnitude of their estimates will then be determined by the relative strength and frequency of the heterogeneous effects experienced by United and American.

The empirical difference between Dai et al (2010) and this study can be summarized by understanding the counterfactual in each. In Dai et al. (2010), a carrier in an initially competitive market is the counterfactual for a carrier in an initially oligopolistic market, regardless of carrier origin airport capacity share. Their study compares the response of price dispersion to entry in concentrated markets to the response in highly competitive markets to discern the relative importance of competition and the incentive compatibility constraint.

In this study, the counterfactual for a dominant airline on a given route is a non-dominant airline operating on the same route. Theoretically, this allows the comparison of price dispersion response to entry of dominant carriers with valuable FFP, to non-dominant carriers with relatively less valuable FFP on the same route. At the very least, this allows determination of whether airlines can use market dominance to prevent price convergence in the case of increasing competition.

Data

Airline ticket price data come from the DB1B database, a 10% random sample of all US domestic airfares. The dataset is a panel from 1993:Q1 to 2010:Q3. Each observation is an itinerary that, in addition to ticket price, includes the operating airline, origin and destination airports, route distance, fare class, number of passengers, and whether the ticket was one-way or round-trip. A route is defined as two endpoint cities rather than airports. Denver to Midway and Denver to O'Hare are not, for example, considered different routes since it is assumed travelers will consider both Midway and O'Hare when flying to or from Chicago.

In order to minimize differences in ticket cost and quality the tickets used include only coach fares for direct flights. Following convention in the literature round trip ticket prices are divided in half so that the data is constituted of only one-way ticket prices for direct flights [Borenstein Rose (1994); Goolsbee and Syverson (2008); Gerardi and Shapiro (2009)]. An example of a single observation would be a one-way United Airlines flight from Denver to Chicago the 1st Quarter of 2010. As previously stated, a one-way, United flight from Chicago to Denver is considered to be a different observation. This is necessary because an airline's airport capacity share is only a determinant of its FFP value for flyers originating in that city (i.e. United should be able charge higher markups on flights departing Denver to Chicago than the reverse since it is the single dominant carrier in Denver but shares dominance with American Airlines in Chicago). For visualization there is a distribution of United Airline's ticket prices from LAX (Las Angeles) to O'Hare (Chicago) in the 1st quarter of 1995 titled, Histogram 1 in the *Tables and Figures* section.

Dependent variables are average fare, fare percentiles, and the Gini coefficient, a measure of price dispersion. The expected difference between two randomly selected fares on a carrier-route is equal to two times the Gini coefficient multiplied by the airline's average price on that route. For example, if United's Gini coefficient on the Denver to Chicago route is 0.33 and the average ticket price is $400, then 2*0.33*$400 = $264, is the expected difference between two randomly selected United, coach-class fares on this route. There are 109,734 carrier-route observations in the entire panel.

The 80th percentile is treated as the representative premium fare for business travelers and the 20th percentile as the representative discount fare or base fare for leisure travelers. While changes in the Gini coefficient measure whether price dispersion is increasing or decreasing, price percentiles can demonstrate whether the cause is due to changes in the premium fares, discount fares or both.

Finally, collapsed carrier-route-quarter DB1B data is merged with carrier-segment data from the T-100 database which allows the calculation of airline capacity shares (and dominance) at airports. The T-100 database provides quarterly enplanements, total capacity offering in terms of seats and the number of airplanes flown by each carrier. Fortunately, the T-100 database is quite extensive. The merge is successful for 90% of the carrier-route observations. For robustness, it is verified that regression coefficients do not change depending on whether market share is measured in terms of enplanements, seat capacity, or number of flights.

Intuition for the Heterogeneous Effects of Entry on Price Dispersion

The Role of FFP

An airline with dominant airport capacity share offers more frequent flights and flights to a larger number of destinations from that airport. The larger menu of options on which customers can earn points, redeem rewards and enjoy perk benefits increases the value of a dominant carrier's FFP and elite status relative to non-dominant airlines. In an airport with no single dominant airline, high-value consumers may be evenly distributed among carrier FFPs or subscribe to multiple programs simultaneously. Conversely, airports with a single dominant carrier likely have a large proportion of high-value consumers enrolled in their own loyalty program. In this instance, increasing competition could result in a dominant airline reducing base fares disproportionately more than premium fares and potentially, increasing its price dispersion. If non-dominant airline's price dispersion still decreases with entry, models assuming monotonicity would still find that the standard narrative holds, since non-dominant carriers constitute the majority of the observations. This is what is found in Gerardi and Shapiro (2009)

If the combination of market power *and* frequent flyer programs is an important factor in preserving price discrimination then, as previously stated, the insular effect of airport dominance may be more exaggerated on routes with greater preference heterogeneity. Namely, on routes that service large numbers of both business and leisure travelers as compared to predominantly leisure travelers. This is because an FFP only actually entices business traveling, elite status members to pay significant premiums on fares. Since elite status memberships are constituted primarily of business travelers, FFP should be most effective on routes with high levels of business traffic. A smaller decrease in the 80^{th} price percentile may be observed for a dominant carrier on routes between two large cities than for that same dominant carrier on other routes. Percentage decreases in a dominant carrier's 20^{th} fare percentile should not be different across routes, however. Essentially, if FFP matter, then a dominant airline's reduction in price dispersion with entry should be smaller on routes between two large cities than on other routes.

Similarly, the insular effect of a dominant airlines' FFP should be more pronounced on long-haul routes than short-haul routes. This is partially because, benefits offered to elite status members including seat upgrades, members-only airport lounges and free alcohol are more appealing on longer flights. Additionally, a member's opportunity cost of switching airlines, in the number of miles accrued, is greater on long flights. The cost of switching is especially large for elite status members, who accrue bonus miles,[11] and who are likely to purchase tickets with an airline-specific rewards credit card that earns an additional two miles per dollar spent. The airline-specific rewards credit cards are extra valuable since they allow all reward miles, whether earned by flying or spending, to accrue to the same mileage account. The end result is that, when faced with increasing competition, it should be easier for dominant airlines to continue charging high premiums to elite

[11] Up to 2 miles for each mile actually flown

status members on long-haul routes (where the switching costs are highest) than short-haul routes.

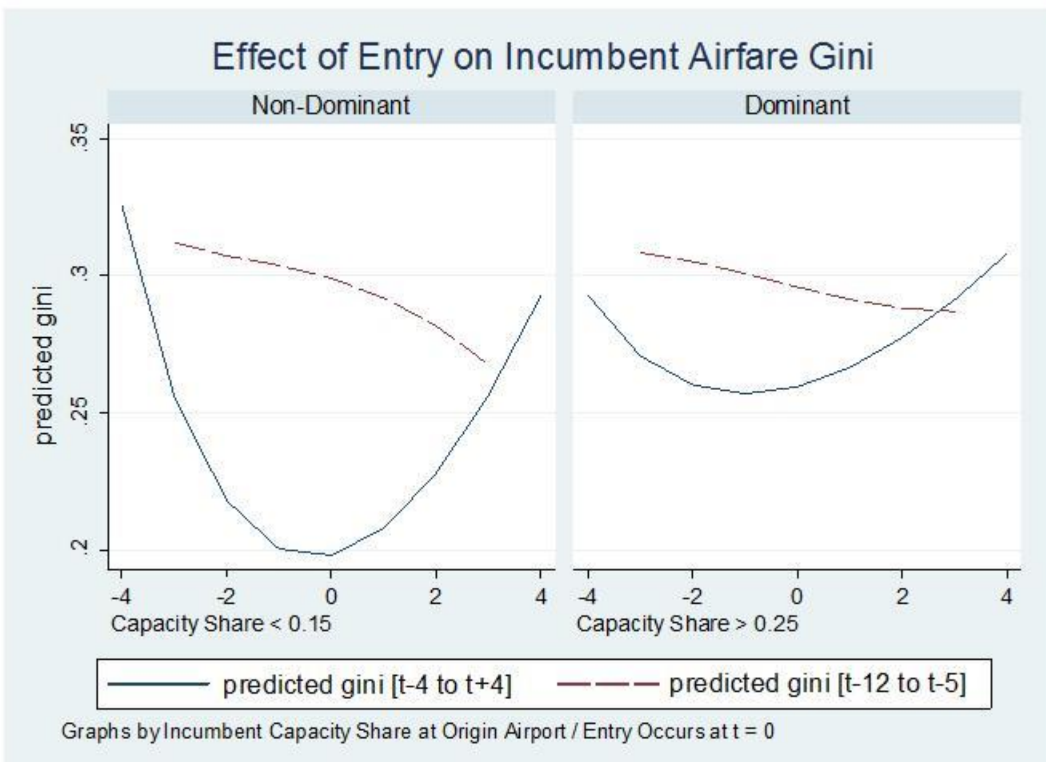
In summary, this paper will examine the different responses of price dispersion to entry for dominant and non-dominant incumbents to determine the importance of market power in preserving price discrimination. To assess the importance of FFP, however, a dominant airline's response to entry is examined across route types. The analysis on dominant airlines looks to see whether price dispersion is reduced less on long-haul and high business traffic routes than on short-haul and leisure routes. By focusing solely on dominant carriers it is theoretically possible to differentiate the importance of FFP and airport dominance on fare response to entry.

Descriptive Statistics

In order to motivate analysis a series of industry snapshots are presented. Figure 1 shows incumbents' predicted Gini coefficients before and after an entry occurs. The graph on the left is for non-dominant airlines while the right is for those which are dominant. Dominance is determined by an airline's capacity share at a route's origin airport. Dominant airlines are those which are responsible for more than 25% of the total capacity in terms of seat offerings from the origin airport. Each of the curves below represents the predicted Gini coefficient of incumbents' airfare from a fit plot using a fractional polynomial function. The solid blue lines predict the Gini coefficients of carrier-route observations which experience an entry within four quarters [$t_0 - 4$ to $t_0 + 4$]. Figure 1 does not distinguish entry by type of entrant. t_0, or $t = 0$, implies an entry of any sort. The dotted maroon lines predict Gini coefficients for the same carrier-route between twelve and five quarters before entry [$t_0 - 12$ to $t_0 - 5$]. These estimates are overlaid to illuminate pre-existing trends.

It is clear from the figure that there is a general downward trend in the Gini coefficient. The predicted trends for Gini coefficients from quarters $t_0 - 12$ through $t_0 - 5$ are relatively similar for both dominant and non-dominant carriers.

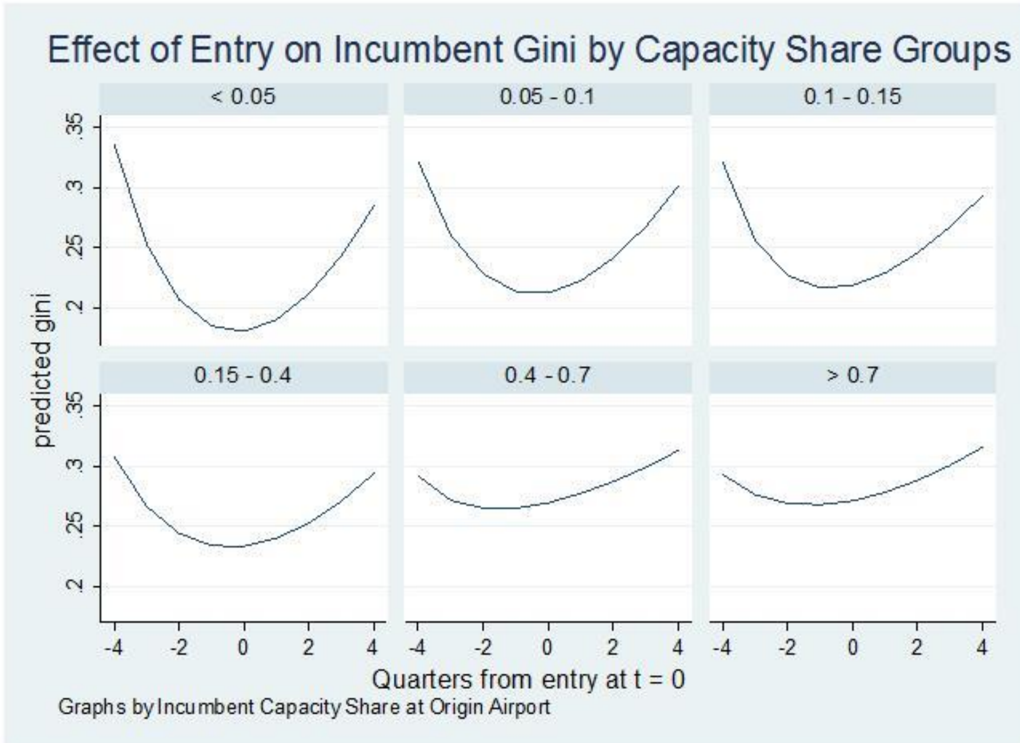
Figure 1



In the periods more immediately preceding entry, the predicted Gini coefficient drops drastically relative to periods further away. This is true regardless of origin airport capacity share, although the dip is much larger for non-dominant carriers. It is surprising to note that the Gini coefficients begin to rise again after entry. This may occur for two reasons. First, a large proportion of market entry in the airline industry is sustained for a short time; several quarters or less. The entry variable used here does not distinguish between entrants that stayed on the route and those that exited shortly thereafter. Second, the trends may be revealing that airlines react sharply to the threat (or announcement) of entry but revert to previous pricing regimes (at least in terms of overall dispersion) after entry has occurred. These trends are consistent even when entry is split into different types. See Figure 1 continued in the *Tables and Figures* section, which shows the effect on the Gini coefficient of LCC entry, LGC entry and *both* entry.

Figure 2 examines the correlation between entry and the Gini coefficient for six buckets of capacity share at the origin airport. This figure confirms the likely existence of heterogeneous effects of entry on price dispersion. The decrease in the predicted Gini coefficient with entry is largest for carriers with the smallest capacity shares at the origin airport, those with less than 5%. The decrease in the predicted Gini coefficient associated with entry becomes gradually smaller as capacity share at the origin airport increases. The smallest decrease occurs among incumbents responsible for more than 70% of an origin airport's capacity share.

Figure 2



Examining predicted curves it is difficult to infer exactly how far in advance of entry an incumbent's Gini coefficient is actually decreasing. It is clearer when the predicted Gini coefficient is examined in just the four quarters preceding entry. This is displayed in figure 3. Here, it is possible to make out more precisely that an incumbent's Gini begins decreasing somewhere between two and three quarters before entry.

While illuminating, price dispersion snapshots tell only part of the story. If a dominant carrier's FFP, and not just airport dominance, are preserving its ability to price discriminate then one would expect to see other patterns as well. If dominant carriers disproportionately reduce premium fares less than base fares in response to entry, relative to non-dominant ones, it could be that FFP help dominant carriers

Figure 3

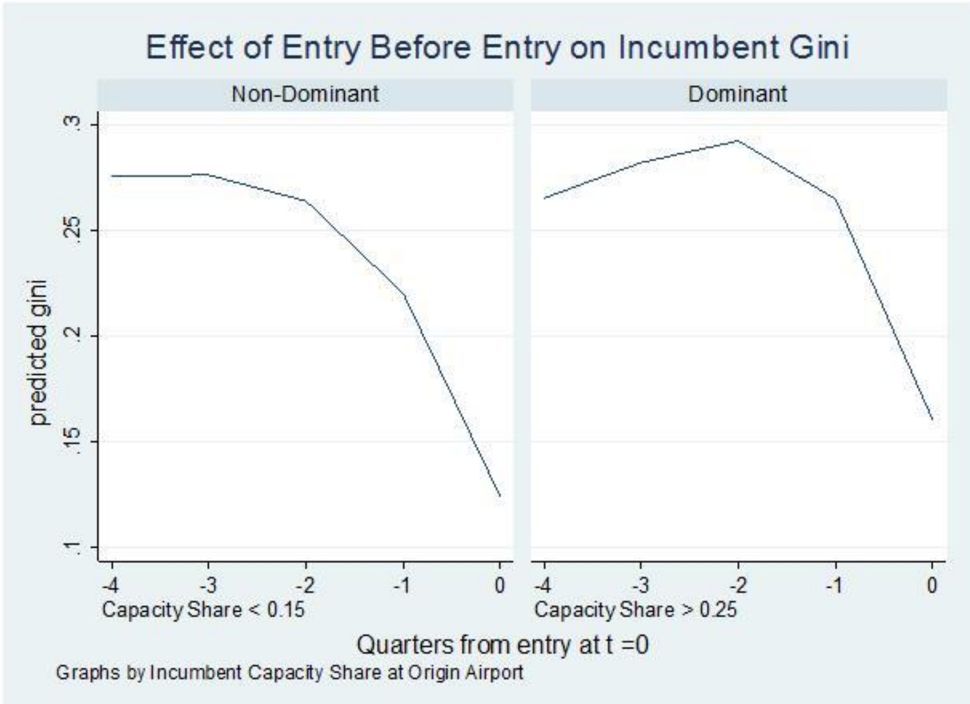
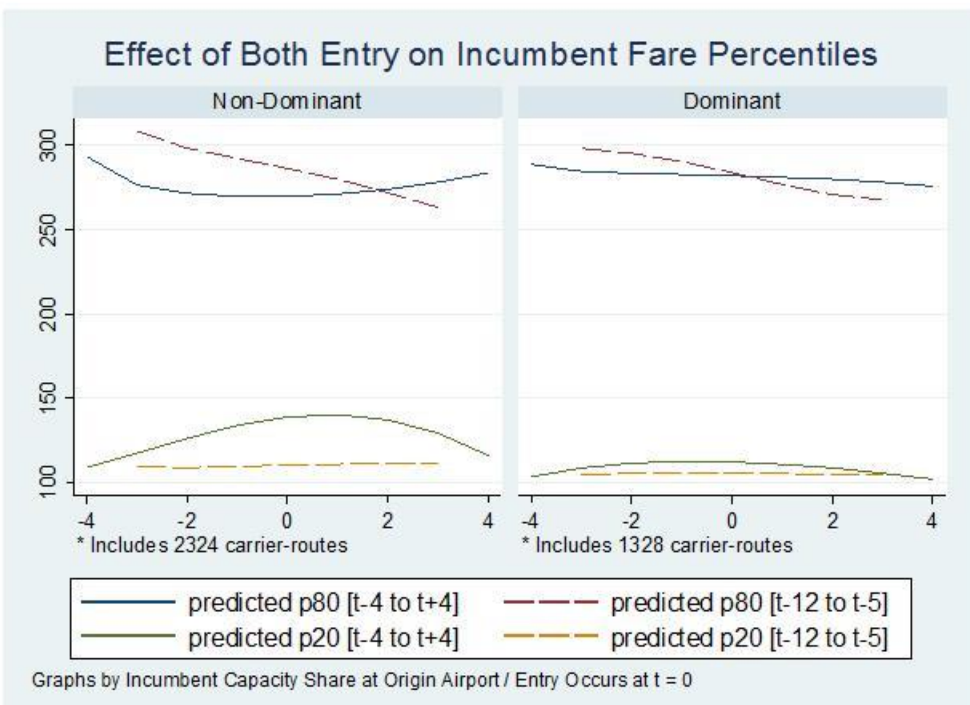


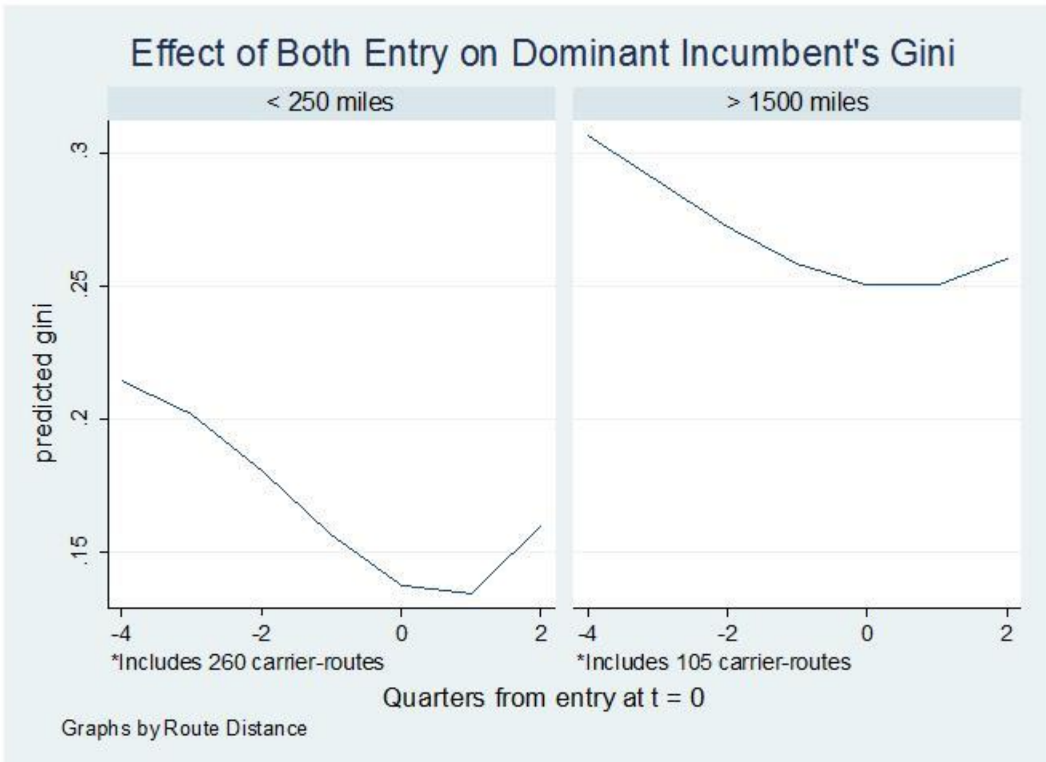
Figure 4



continue to charge premiums to high-end customers. Figure 4 explores whether there is descriptive evidence of this. The correlation between entry and 80th and 20th fare percentiles is shown. Entry in this instance is entry of both an LGC and an LCC in the same quarter. Again, predicted Gini twelve to five quarters before entry is overlaid with maroon dotted lines to illuminate pre-existing trends. The 80th and 20th fare percentiles of dominant carriers change very little change from quarters [t -12, t -5] to quarters [t – 4, t + 4]. In particular, the 80th percentile does not appear to drop with entry. By contrast, the 80th fare percentile fornon-dominant carrier's appears to drop $25-30 in quarters preceding entry (starting at about t_0 – 3). Also, the 20th fare percentile appears to be increasing for non-dominant carriers in the quarters preceding entry and decreasing afterwards, relative to preexisting trends. Decreases in the 80th fare percentile and increases in the 20th fare percentile result in a contraction of price dispersion for non-dominant carriers relative to dominant ones. The trends are similar, although less pronounced when the entrant is either a legacy or a low cost carrier alone.

Next, the relationship between price dispersion and dominant carrier route type is examined. A previously stated hypothesis, is that FFP may cause dominant carriers to experience smaller decreases in price dispersion on long-haul routes and routes between major cities; in fact, figures 5 and 6 show that this may be the case. Again, entry is defined as entry of both an LGC and an LCC in the same quarter. The pre-entry Gini coefficient is smaller for short-haul routes than long-haul routes, which we would expect. Airlines use bigger planes for longer flights which allows them to allocate seats to a larger number of fare classes and price discriminate more effectively.

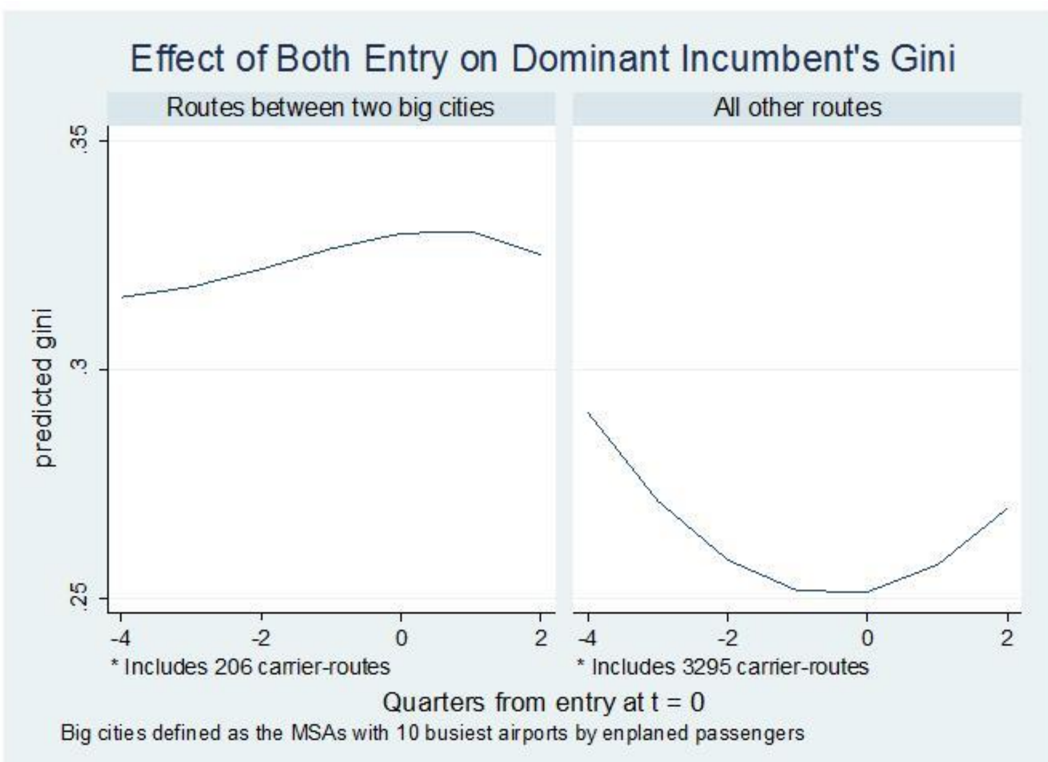
Figure 5



Even though pre-entry price dispersion is larger on long-haul routes, however, the contraction in fares with entry is greatest on short-haul flights. The predicted Gini coefficient decreases by roughly 0.05 for long-haul flights but clearly decreases by more than 0.05 for short-haul flights. This is consistent with the notion that dominant carriers' FFPs are more effective at preserving price discrimination on long-haul routes. This is expected since an elite member's airline switching cost, in terms of miles accrued, is greater on long flights.

Another hypothesis was that, routes between big cities serve high volumes of business travelers, including the majority of elite status members, and a dominant carrier's FFP should therefore cause premium fares to decrease disproportionately less than base fares in response to entry. Again, figure 6 presents descriptive evidence that this occurs. The heterogeneity is more pronounced than in the comparison of long-haul and short-haul routes. Entry is defined as entry of both an LGC and an LCC in the same quarter. Dominant carriers' price dispersion actually increases with entry on routes between two big cities while on all other routes predicted Gini decreases.

Figure 6



This is consistent with the possibility that FFP insulate premium fares from the effect of competition for dominant carriers on routes between big cities. Dominant carriers on these routes may respond to entry predominantly by reducing prices of low-end fares. This trend is the same when entry is defined as only an LGC or only an LCC.

Empirical Model

The descriptive trends clearly demonstrate the possibility of heterogeneous and even non-monotonic effects of competition on price dispersion. They indicate that the magnitude and direction of the effect of entry may be dependent on incumbents' origin airport market share and route type. A rigorous analysis is now conducted to determine whether these trends are rooted in causal mechanisms. First, a linear model assuming monotonicity, similar to ones used in previous studies, [Borenstein and Rose (1994); Gerardi and Shapiro (2009)] is employed to estimate the effect of entry on price dispersion; the assumption of monotonicity does not permit the model to estimate an effect that varies by market share or route type.

$$Y_{ijkt} = \Phi_{i,t+r}\mathrm{ENTRANT}_{j,t+r} + X_{j(k)t} + \alpha_{ij} + \delta_{it} + \eta_{ijt} \tag{1}$$

Y_{ijkt} is the Gini coefficient of price dispersion, for carrier i on route j, from origin airport k, in quarter t. The dependent variable is restricted to legacy airlines. $\mathrm{ENTRANT}_{j,t+r}$ is a series of dummy variables for quarters $t_0 \pm r$ before, after and including entry at t_0. These dummy variables are mutually exclusive and cannot be interpreted additively as will be explained below. α_{ij} is a complete set of carrier-route fixed effects while $\boldsymbol{\delta}_{it}$ is a complete set of carrier-quarter fixed effects. $\mathbf{X}_{j(k)t}$ are additional route or (airport-specific) controls that vary over time including the number of enplaned passengers at an airport and the number of competitors on a route in quarter $t_0 - 1$. η_{ijt} is assumed to be an *i.i.d* normally distributed error term.

The total number of passengers at origin airport k each quarter is included to capture idiosyncratic variation in airport-specific demand over time. At least two studies on airline price dispersion have identified enplaned passengers on a route as a measure of demand and used it as an instrument for the number of competitors or market concentration [Gerardi and Shapiro (2009); Dai et al. (2010)]. In contrast, the assertion of this paper is that market demand is likely an important determinant of price dispersion in its own right and belongs in the primary regression. To facilitate comparison with previous work, however, this initial model is also estimated using enplaned passengers as an instrument for competition. $X_{j(k)t}$ includes the lagged number of airlines on a route in order to control for the initial intensity of competition preceding entry.

A second model uses several dummy variables to differentiate between the effects of entry by low cost carriers (LCC), legacy carriers (LGC) or both. It is the following:

$$Y_{ijkt} = \Phi_{t+r}\text{LCC\_ENT}_{j,t+r} + \Psi_{t+r}\text{LGC\_ENT}_{j,t+r} + \lambda_{t+r}\text{Both\_ENT}_{j,t+r} + X_{j(k)t} + \alpha_{ij} + \delta_{it} + \eta_{ijkt} \quad (2)$$

Y_{ijkt} is the Gini coefficient of fare dispersion. The fixed effects and additional controls are the same as in equation (1). $\text{LCC\_ENT}_{j,t+r}$, $\text{LGC\_ENT}_{j,t+r}$, and $\text{Both\_ENT}_{j,t+r}$ are each series of dummy variables for quarters $t_0 \pm r$ before and after entry and inclusive of quarter t_0 when entry occurs. This specification creates three sets of mutually exclusive dummy variables. Again, the coefficients on these dummies are not interpreted additively. The coefficients on entry dummies give an airline's level of price dispersion at time $t_0 \pm r$ relative to its price dispersion in periods more than $t_0 \pm r$ quarters before or after any form of entry (LCC, LGC, or both). Since all quarters outside the window $t_0 \pm r$ are excluded from the regression, they are simply referred to as the excluded period. The following is an illustrative example of LCC entry on the price dispersion,

$$\text{Gini}_{ijk,t} = \ldots \quad (-0.0008)\text{LCC\_ENT}_{j,t} + (-0.0318)\text{LCC\_ENT}_{j,t+1}$$

The results would be interpreted as follows: In the quarter of entry, t_0, carrier *i's* Gini is 0.0008 less than in the excluded period. One quarter after entry, carrier *i's* Gini is 0.0318 less than in the excluded period. The estimated effect of LCC entry, from t_0 to $t_0 + 1$, is the difference in coefficients on ENT_t and ENT_{t+1}. In this case, LCC entry reduces incumbent Gini by (-0.0318) – (-0.0008) = -0.031 from quarter t_0 to $t_0 + 1$, although -0.0318 can still be interpreted as the total effect of entry. Assuming average fare of $300, this means that after entry, the average difference between two randomly selected fares on this route is $18.60 (0.031*2*$300=$18.60) less than it was before entry. Additionally, if the average Gini coefficient is 0.22, then this represents a 14% reduction in price dispersion.

In the preferred specifications, the assumption of a homogeneous, monotonic effect of entry on price dispersion is relaxed and the effect of entry is estimated separately for dominant and non-dominant airlines. A more flexible model is created by interacting entry with dummy variables for buckets of origin airport capacity share. Dummy variables for capacity share are created for incumbents with less than 15% share, with 15-50% share, 50-75% share and with greater than 75% share. Incumbents with less than 15% share are considered to have non-dominant status. Time dummies are still included for each quarter three years before, and one year after entry, $t_0 - 12$ to $t_0 + 4$. The model, therefore, compares incumbent fares in the quarter of entry and each of sixteen quarters surrounding entry to the excluded period. This extensive set of dummies exists for each entrant type, LGC, LCC and both. This results in 51 individual dummy variables which are then interacted with dummy variables for four categories of origin airport capacity share. The regression thus includes a total of 204 dummy variables for entry on the right hand side (17 quarters x 3 entrant types x 4 capacity share categories = 204).

$$Y_{ijkt} = \Phi_{D,t+r}(\mathrm{LCC\_ENT}_{j,t+r} * D^{1,2,3,4}_{i,k,t}) + \Psi_{D,t+r}(\mathrm{LGC\_ENT}_{j,t+r} * D^{1,2,3,4}_{i,k,t}) + \lambda_{D,t+r}(\mathrm{Both\_ENT}_{j,t+r} * D^{1,2,3,4}_{i,k,t}) + X_{j(k)t} + \alpha_{ij} + \delta_{it} + \eta_{ijkt} \quad (3)$$

Y_{ijkt} is still the Gini coefficient of fare dispersion. Equation (3) includes the same fixed effects and controls as equations (1) and (2). $D^{1,2,3,4}_{i,k,t}$ are the set of dummy variables indicating an incumbents capacity share at the origin airport. For example, $D^{1}_{i,k,t}$ equals 1 when incumbent i has less than 15% capacity share at airport k in quarter t and 0 otherwise, $D^{2}_{i,k,t}$ equals 1 when incumbent i has between 15 – 50% capacity share and $D^{3}_{i,k,t}$ equals 1 when incumbent i has between 50 – 75% capacity share etc. This specification allows the estimated effects of entry to be heterogeneous by origin airport capacity share. Evidence of heterogeneous effects exists if the coefficients on entry dummies interacted with different capacity share buckets are different from each other and also statistically different from zero. The effects of entry are non-monotonic if some coefficients are negative and others are positive.

In order to understand what is causing price dispersion to change, 80th and 20th fare percentiles are used as dependent variables in subsequent estimations of the regression equation. In these regressions, a slightly altered version of equation (3) is re-estimated. Now incumbents with less than 15% airport capacity share are considered non-dominant and incumbents with greater than 25% share are dominant; essentially, only two dummies for origin capacity share are used instead of four.

$$Y_{ijkt} = \Phi_{D,t+r}(LCC\_ENT_{j,t+r} * D^{1,2}_{i,k,t}) + \Psi_{D,t+r}(LGC\_ENT_{j,t+r} * D^{1,2}_{i,k,t}) + \lambda_{D,t+r}(Both\_ENT_{j,t+r} * D^{1,2,}_{i,k,t}) + X_{j(k)t} + \alpha_{ij} + \delta_{it} + \eta_{ijkt} \quad (4)$$

Y_{ijkt} is now the natural log of the 80th or 20th fare percentile. Equation (4) includes the same fixed effects and controls as equations (1), (2) and (3). $D^{1}_{i,k,t}$ equals 1 when incumbent I has less than 15% capacity share at airport k in quarter t and 0 otherwise, $D^{2}_{i,k,t}$ equals 1 when incumbent i has greater than 25 capacity share.

Primary Results

Heterogeneous Effects of Entry by Origin Capacity Share

Column (1) of Table 1 presents the estimates of specification (1) using the Gini coefficient of airfares on carrier-routes that face an entrant of undefined type. The model is inflexible and assumes that the effect of entry is homogeneous and monotonic. Additionally, it looks only at the effect of entry in the quarter it occurs, as in Gerardi and Shapiro (2009). There is a negative and statistically significant effect of entry on price dispersion. Entry is predicted to decrease the Gini coefficient by 0.007, or 3.3% of average price dispersion. This estimate is not meaningfully different from the un-instrumented estimates of entry in a similar model found by Gerardi and Shapiro (2009).

In column (2), enplaned passengers are used as instruments for entry on a route. As in Gerardi and Shapiro (2009), this substantially increases the estimated coefficients on entry to -0.267, or 127% of average price dispersion. This estimate is nonsensically large but still smaller in magnitude than the estimates found by Gerardi and Shapiro (2009) using the same instruments. When the model employs year-quarter fixed effects instead of carrier-quarter fixed effects the estimates become even larger and are no longer substantially different from those found by Gerardi and Shapiro (2009). To restate, the assertion of this paper is that this instrument does not satisfy the exclusion restriction and should result in an overestimate of the magnitude of the effect of entry.

Table 1 Incumbent Responses To Entry

VARIABLES	(1) Gini	(2) Gini w/ G & S Instrument	(3) Gini w/ new Instrument	(4) Gini
Entry	-0.006***	-0.267***	-0.24***	
t_0 (only)	(0.0007)	(0.0822)	(0.029)	
Entry				-0.0007
$t_0 - 3$				(0.0005)
Entry				-0.001**
$t_0 - 2$				(0.0004)
Entry				-0.002***
$t_0 - 1$				(0.0005)
Entry				0.0002
t_0				(0.0006)
Entry				-0.001**
$t_0 + 1$				(0.0005)
Entry				-0.001***
$t_0 + 2$				(0.0005)
Ln Enplaned passengers	0.012***			0.006***
Origin airport	(0.001)			(0.001)
Number of competitors	0.0002	0.0559***	0.049***	-0.002***
	(0.0004)	(0.0175)	(0.006)	(0.0004)
Observations	81,819	81,819	81,819	63,017
R-squared	0.132			0.264
Number of carrier-routes	3,601	3,601	3,601	1,561

Notes. The dependent variable in columns (1) (2) (3) and (4) is the Gini coefficient of fare dispersion for legacy airlines: American, Continental, Delta, Northwest, United and US Airways. All regressions include carrier-route and carrier-year-quarter fixed effects. The sample includes non-stop flights on 90% of the domestic routes served by these airlines. Entry is an indicator variable equal to one if entry of any kind occurred on route j in quarter t_0 and zero otherwise. The coefficients on Entry are interpreted as the effect of entry in quarter $t_0 \pm r$ compared to the excluded periods, quarters greater and less than $t_0 \pm r$. Robust standard errors are in parentheses and are clustered by carrier-route *** p<0.01, ** p<0.05, * p<0.1.

In column (3) enplaned passengers at the origin airport is used to instrument for entry; this which was proposed as a possibly superior instrument. The estimated coefficients *are* smaller in magnitude but still unreasonably large and similar to those in column (2).

Column (4) presents the results of specification (1) when it is modeled as a short event study. Entry dummies are expanded to include five quarters around entry. The effects of entry are examined beginning three quarters before entry, $t_0 - 3$ through two quarters after entry, $t_0 + 2$. In this specification, the coefficients on

Entry_{t-2} and Entry_{t-1} are negative and statistically significant. This indicates that for incumbents facing an entrant in t_0, price dispersion is lower and statistically significant in quarters $t_0 - 2$ and $t_0 - 1$ than in the quarters excluded from the event study. The coefficient on Entry_{t-3} is negative but not statistically different from price dispersion in the excluded quarters. This seems to imply that price dispersion starts decreasing somewhere between two and three quarters prior to entry, corresponding to trends observed in the descriptive figures. Also, it is consistent with anecdotes that airlines typically announce entry on a route approximately six months in advance. In the quarter entry occurs, price dispersion actually increasing slightly relative to quarter $t_0 - 1$; price dispersion is again decreasing in the quarters after entry. The largest estimate of the effect of entry on the Gini coefficient is -0.002, nearly 1% of average initial price dispersion.

Table 2 presents the estimates from specification (2). Here, entry is broken into three categories, entry by an LGC (legacy carrier), an LCC (low cost carrier), and *both* in the same quarter. This model is an event study and includes dummies including and surrounding entry from $t_0 - 3$ to $t_0 + 2$. The model remains inflexible, however, and the estimates on entry are still required to be homogeneous and monotonic. The dependent variable in column (1) is Gini coefficient while columns (2) and (3) are natural logs of the 80^{th} and 20^{th} fare percentiles.

Again, incumbent price dispersion is decreasing and statistically significant in quarters $t_0 - 2$ and $t_0 - 1$ whether the entrant is LGC or *both*. Carrier-route Gini coefficient decreases by as much as 0.013 when both entry occurs. This constitutes a 6% decrease in price dispersion. Similar to the before, price dispersion increases in t_0 relative to $t_0 - 1$; price dispersion is still lower in t_0 than in the excluded periods. Price dispersion decreases further in quarters $t_0 + 1$ and $t_0 + 2$. The point estimates of low cost carrier entry on price dispersion are positive but small and statistically insignificant. Still, this result provides some evidence that the effect of entry on price dispersion may be non-monotonic depending on entrant type.

Table 2 further shows that incumbents decrease in price dispersion in quarters $t_0 - 2$, $t_0 - 1$, and $t_0 + 1$, $t_0 + 2$ is driven predominantly by decreases in the 80th fare percentile. Although both the 80th and the 20th fare percentiles are decreasing with all types of entry, decreases in the 80th percentile are generally larger in percent and absolute terms. The 80th percentile decreases by as much as 4% in the quarters preceding entry of *both* carrier types.

Table 2 Incumbent Responses To Entry By Entrant Type

VARIABLES	(1) Gini	(2) Ln(p80)	(3) Ln(p20)
LGC entry	-0.001**	-0.006*	0.001
$t_0 - 3$	(0.0005)	(0.003)	(0.002)
LGC entry	-0.003***	-0.012***	-0.007**
$t_0 - 2$	(0.0005)	(0.003)	(0.003)
LGC entry	-0.004***	-0.02***	-0.014***
$t_0 - 1$	(0.0006)	(0.003)	(0.003)
LGC entry	-0.002***	-0.006	0.003
t_0	(0.0007)	(0.005)	(0.004)
LGC entry	-0.003***	-0.01**	-0.009**
$t_0 + 1$	(0.0006)	(0.004)	(0.003)
LGC entry	-0.003***	-0.005	-0.01***
$t_0 + 2$	(0.0005)	(0.004)	(0.003)
LCC entry	0.002*	0.0001	-0.002
$t_0 - 3$	(0.0009)	(0.004)	(0.003)
LCC entry	0.0006	-0.008	-0.01**

$t_0 - 2$	(0.0001)	(0.005)	(0.003)
LCC entry	0.001	-0.013**	-0.014**
$t_0 - 1$	(0.001)	(0.005)	(0.005)
LCC entry	0.003**	-0.017**	-0.009**
t_0	(0.001)	(0.007)	(0.005)
LCC entry	0.002*	-0.028***	-0.02***
$t_0 + 1$	(0.0009)	(0.006)	(0.005)
LCC entry	0.0005	-0.027***	-0.02***
$t_0 + 2$	(0.0009)	(0.006)	(0.005)
Both entry	-0.008***	0.015	0.02***
$t_0 - 3$	(0.001)	(0.009)	(0.006)
Both entry	-0.008***	-0.012	0.007
$t_0 - 2$	(0.001)	(0.007)	(0.005)
Both entry	-0.013***	-0.04***	-0.018**
$t_0 - 1$	(0.001)	(0.007)	(0.008)
Both entry	-0.003*	-0.018	0.004
t_0	(0.001)	(0.012)	(0.009)
Both entry	-0.012***	-0.025**	-0.012
$t_0 + 1$	(0.001)	(0.01)	(0.008)
Both entry	-0.009***	-0.024**	-0.026***
$t_0 + 2$	(0.001)	(0.01)	(0.008)
Number of competitors	-0.001***	-0.038***	-0.024***
	(0.0004)	(0.003)	(0.002)
Ln Enplaned passengers	0.006***	-0.025**	-0.037***
At Origin Airport	(0.001)	(0.01)	(0.009)
Observations	67,585	67,595	67,595
R-squared	0.200	0.176	0.129
Number of carrier-routes	2,064	2,067	2,067

Notes. The dependent variable in column (1) is the Gini coefficient of fare dispersion, (2) is the 80th fare *(continued)* percentile, and (3) is the 20th fare percentile for legacy airlines: American, Continental, Delta, Northwest, United and US Airways. All regressions include carrier-route and carrier-year-quarter fixed effects. The sample includes non-stop flights on 90% of the domestic routes served by these airlines. Entry is an indicator variable equal to one if entry of any kind occurred on route *j* in quarter t_0 and zero otherwise. The coefficients on Entry are interpreted as the effect of entry in quarter $t_0 \pm r$ compared to the excluded periods, quarters greater and less than $t_0 \pm r$. Robust standard errors are in parentheses and are clustered by carrier-route Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3 presents estimates from the preferred model, specification (3). Now, modeled as a flexible long range event study. Entry dummies are included for all seventeen quarters (four years) around and including each occurrence of entry. Abbreviated results from t_{-10} to $t + _4$ are displayed. The effects of entry are now permitted to vary by incumbent capacity share at the origin airport. Again, the effects of LGC entry and *both* entry are generally negative and often statistically significant. The only types of entry that lead to meaningful and statistically significant decreases in price dispersion are LGC entry and *both* entry [shaded for emphasis]. Additionally, however, it is only non-dominant airlines with less than 15% capacity share or 15-25% capacity share that show statistically significant decreases in price dispersion. Altogether, non-dominant airlines constitute over 60% of the panel observations. The effects of entry are larger on the set of incumbents with less than 15% capacity share than those with 15-25% share. *Both entry* decreases Gini by as much as 0.022, 10% of average price dispersion for airlines with less than 15% capacity share and by as much as 0.006, about 2.5% of average price dispersion for those with 15-25% share. LGC entry decreases Gini by as much as 0.005 for those with less than 15% share and 0.003 for those with 15-25% share.

Table 3 INCUMBENT RESPONSES TO ENTRY BY ENTRANT TYPE

VARIABLES *Origin Capacity Share*	(1) Gini < 0.15	(2) Gini 0.15 – 0.25	(3) Gini 0.25 – 0.75	(4) Gini > 0.75
LGC entry	-0.001	-0.002*	0.0001	-0.002
$t_0 - 10$	(0.001)	(0.001)	(0.001)	(0.002)
LGC entry	-0.002*	-0.001	0.0005	-0.002
$t_0 - 9$	(0.001)	(0.001)	(0.001)	(0.002)
LGC entry	-0.002*	-0.001	-0.0002	-0.002
$t_0 - 8$	(0.001)	(0.001)	(0.001)	(0.001)
LGC entry	-0.001	-0.0006	-0.001	0.0004
$t_0 - 7$	(0.001)	(0.001)	(0.001)	(0.002)
LGC entry	-0.002*	-0.003**	-0.002**	-0.001
$t_0 - 6$	(0.001)	(0.001)	(0.001)	(0.002)
LGC entry	-0.002*	-0.003***	-0.003***	-0.001
$t_0 - 5$	(0.001)	(0.001)	(0.001)	(0.002)
LGC entry	-0.002*	-0.003***	-0.003***	-0.002
$t_0 - 4$	(0.001)	(0.001)	(0.001)	(0.002)
LGC entry	-0.0008	-0.001	-0.001*	0.002
$t_0 - 3$	(0.001)	(0.0009)	(0.0007)	(0.001)
LGC entry	-0.003***	-0.002	-0.001**	0.003*
$t_0 - 2$	(0.001)	(0.001)	(0.0008)	(0.001)
LGC entry	-0.005***	-0.002*	-0.002**	0.002
$t_0 - 1$	(0.001)	(0.001)	(0.0008)	(0.001)
LGC entry	-0.003**	-0.003**	0.002*	0.0006
t_0	(0.001)	(0.001)	(0.001)	(0.002)
LGC entry	-0.005***	-0.002*	-0.001	0.001
$t_0 + 1$	(0.001)	(0.001)	(0.0008)	(0.001)
LGC entry	-0.003***	-0.0006	-0.0009	0.0005
$t_0 + 2$	(0.001)	(0.001)	(0.0008)	(0.001)
LGC entry	-0.0006	-0.002	-0.003***	0.0006
$t_0 + 3$	(0.001)	(0.001)	(0.001)	(0.002)
LGC entry	-0.0008	-0.0006	-0.003***	-0.0005
$t_0 + 4$	(0.001)	(0.001)	(0.001)	(0.002)
LCC entry	0.004**	-0.0006	0.003**	0.003
$t_0 - 10$	(0.001)	(0.001)	(0.001)	(0.005)
LCC entry	0.004***	-0.0007	0.004**	-0.0008
$t_0 - 9$	(0.001)	(0.002)	(0.001)	(0.005)
LCC entry	0.003*	0.001	0.0002	0.002
$t_0 - 8$	(0.001)	(0.002)	(0.001)	(0.005)
LCC entry	0.003**	0.0007	-0.0009	0.004
$t_0 - 7$	(0.001)	(0.002)	(0.001)	(0.004)
LCC entry	0.004***	0.001	-0.002	0.007
$t_0 - 6$	(0.001)	(0.002)	(0.001)	(0.005)
LCC entry	0.004**	0.0005	-0.0008	0.006
$t_0 - 5$	(0.001)	(0.002)	(0.001)	(0.005)
LCC entry	0.001	0.001	0.0003	0.013*
$t_0 - 4$	(0.001)	(0.002)	(0.001)	(0.007)
LCC entry	-0.0003	0.002	0.002	0.0004
$t_0 - 3$	(0.001)	(0.001)	(0.001)	(0.003)

LCC entry	0.0003	0.002	0.001	0.001
$t_0 - 2$	(0.001)	(0.001)	(0.001)	(0.003)
LCC entry	-0.002	0.002	0.0001	0.001
$t_0 - 1$	(0.001)	(0.001)	(0.001)	(0.003)
LCC entry	0.001	0.005**	0.002	0.001
t_0	(0.001)	(0.002)	(0.001)	(0.004)
LCC entry	-0.002	0.003*	0.001	0.001
$t_0 + 1$	(0.001)	(0.001)	(0.001)	(0.003)
LCC entry	-0.001	0.003*	0.001	-0.005*
$t_0 + 2$	(0.001)	(0.001)	(0.001)	(0.003)
LCC entry	-0.0001	0.003*	-0.001	0.007*
$t_0 + 3$	(0.001)	(0.002)	(0.001)	(0.003)
LCC entry	-0.0001	0.003*	0.001	0.004
$t_0 + 4$	(0.001)	(0.001)	(0.001)	(0.003)
Both entry	-0.002	0.001	-0.0009	0.000653
$t_0 - 10$	(0.002)	(0.002)	(0.002)	(0.00721)
Both entry	-0.002	0.002	-0.001	0.0105
$t_0 - 9$	(0.002)	(0.003)	(0.002)	(0.00739)
Both entry	-0.002	0.001	0.0003	0.00169
$t_0 - 8$	(0.002)	(0.003)	(0.002)	(0.00837)
Both entry	-0.002	-0.0005	0.0004	-0.00531
$t_0 - 7$	(0.002)	(0.003)	(0.002)	(0.00725)
Both entry	-0.001	0.001	0.004*	-0.00594
$t_0 - 6$	(0.002)	(0.003)	(0.002)	(0.00658)
Both entry	-0.0004	0.0003	0.004*	-0.0162**
$t_0 - 5$	(0.002)	(0.003)	(0.002)	(0.00688)
Both entry	0.0003	-0.001	-0.0004	-0.0129**
$t_0 - 4$	(0.002)	(0.002)	(0.002)	(0.00595)
Both entry	-0.011***	-0.005**	0.002	-0.005
$t_0 - 3$	(0.002)	(0.002)	(0.001)	(0.005)
Both entry	-0.012***	-0.003	0.003	-0.0004
$t_0 - 2$	(0.002)	(0.002)	(0.001)	(0.005)
Both entry	-0.02***	-0.006**	-0.002	-0.005
$t_0 - 1$	(0.003)	(0.002)	(0.001)	(0.005)
Both entry	-0.006**	0.001	0.005**	-0.006
t_0	(0.002)	(0.002)	(0.002)	(0.004)
Both entry	-0.022***	-0.004*	-0.002	-0.001
$t_0 + 1$	(0.003)	(0.002)	(0.001)	(0.004)
Both entry	-0.016***	-0.001	-0.002	-0.005
$t_0 + 2$	(0.003)	(0.002)	(0.001)	(0.005)
Both entry	-0.003*	-0.004	-0.004*	-0.005
$t_0 + 3$	(0.002)	(0.002)	(0.002)	(0.005)
Both entry	-0.002	-0.004	-0.003	-0.008
$t_0 + 4$	(0.002)	(0.003)	(0.002)	(0.005)
Number of competitors	-0.001*	-0.002**	-0.004***	0.0002
$t_0 - 1$	(0.0006)	(0.0008)	(0.0008)	(0.001)
Ln Enplaned passengers	0.006	0.009**	0.021***	0.023***
Origin airport	(0.004)	(0.003)	(0.006)	(0.008)
Observations	32,443	5,279	21,260	3,143

R-squared	0.197	0.221	0.292	0.340
Number of carrier-routes	1,281	344	799	269

Notes. The dependent variable in columns (1)-(4) is the Gini coefficient of fare dispersion for legacy airlines: American, Continental, Delta, Northwest, United and US Airways. Observations are divided into columns based on incumbents capacity share (in terms of seat offerings) at the origin airport. All regressions include carrier-route and carrier-year-quarter fixed effects. The sample includes non-stop flights on 90% of the domestic routes served by these airlines. Entry is an indicator variable equal to one if entry of any kind occurred on route j in quarter t_0 and zero otherwise. The coefficients on Entry are interpreted as the effect of entry in quarter $t_0 \pm r$ compared to the excluded periods, quarters greater and less than $t_0 \pm r$. Robust standard errors are in parentheses and are clustered by carrier-route Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Estimates of LGC and LCC entry on incumbents with greater than 75% capacity share at the origin airport are positive but mostly not statistically significant. In fact, nearly all the estimates of LCC entry on airlines with greater than 25% capacity share are positive, although, few are statistically significant. This offers weak evidence that the effect of entry may be non-monotonic, in this instance depending on origin capacity share. There is again, weak evidence that the effect of entry may also be non-monotonic depending on entrant type.

Table 4 presents results from specification (4), estimating a long range event study as in Table 3. To ease cognitive burden, results are again somewhat abbreviated. Here, non-dominant incumbents are those with less than 15% capacity share and dominant incumbents as those with greater than 25% capacity share. The dependent variables are the natural log of incumbent 80th and 20th fare percentiles. Regressing fare percentiles is meant to add insight as to why price dispersion in Table 3 is decreasing. Both 80th and 20th fare percentiles are decreasing one to three quarters before entry occurs. Although the percentage decreases for the 80th and 20th percentiles are similar, the absolute decrease in fare price is greater for the 80th percentile. Proportionally larger decreases in the 80th

fare percentiles appear to be driving the contraction in fare dispersion observed in Table 3.

There is no obvious story as to why, in Table 3, price dispersion decreases in quarters prior to entry but then increases slightly from $t_0 - 1$ to t_0 before continuing to decrease in quarters $t_0 + 1$ and $t_0 + 2$. In some cases, it may be explained by the fact that fares in the 20th percentile are decreasing more than fares in the 80th percentile from quarter $t_0 - 1$ to t_0. This could be the case if incumbents decrease the price of premium fares on the announcement of a competitor's planned entry in attempt to deter entry or generate consumer loyalty but wait to decrease low-end fares until after entry has occurred. Another possibility, is simply that neither the 80th nor the 20th percentiles is estimated precisely in the quarter entry occurs. In this case, imprecise estimates may be the main reason for the apparent increase in price dispersion from $t_0 - 1$ to t_0.[12]

There is evidence in Table 4 that the effect of the entry on fares is greater for non-dominant than dominant incumbents. LGC entry decreases 80th and 20th fare percentiles for both dominant and non-dominant incumbents, but the magnitude of the estimates is larger for non-dominant carriers. The effects on 20th percentile are substantially different for dominant and non-dominant incumbents. Effects of entry

[12] Estimates in quarter t_0 may be imprecise because they combine the incumbents' response to the "threat of entry" or announced entry and the incumbents' response to the actual entry. Since entry is not likely to occur on the first day of the quarter some of the fare observations for a carrier-route within quarter t_0 correspond to the period before entry and others to the period after entry. This could be problematic for estimating incumbent fare dispersion in quarter t_0 if, for example, incumbents pre-emptively reduce high-end fares to deter entry and only reduce low-end fares once entry has occurred.

on the 80th percentile are only meaningfully different in the quarters after entry. LGC entry decreases the 80th percentile of a non-dominant incumbent by up to 3% and the 20th percentile by as much as 2%.

Although incumbent price dispersion is not impacted in a significant way by LCC entrants, there *are* negative, statistically significantly impacts on fare percentiles. 80th and 20th fare percentiles are decreasing for both dominant and non-dominant incumbents. Again, estimates of LCC entry are larger for non-dominant carriers and meaningfully different from estimates on dominant[13] carriers. Non-dominant incumbents experience an over 4% decrease in the 80th percentile and as much as a 3% decrease in the 20th percentile. By comparison, dominant incumbents' largest decrease is 2.6% for the 80th percentile and 1.4% for the 20th percentile. While all incumbents reduce fares prior to LCC entry, it occurs that dominant carriers begin decreasing low end fares two quarters earlier than non-dominant carriers. This implies that dominant airlines are more aggressive than non-dominant ones in their attempts to deter LCC entry.

Unsurprisingly, reductions in fare percentiles are greatest when *both* entry occurs. The effect is larger for non-dominant carriers although, only occasionally is the difference from the effect for dominant carriers meaningful. Non-dominant carriers' decrease 80th percentile up to 5.5% and the 20th percentile by as much as 4.7%. Dominant carriers' experience a decrease in both the 80th and 20th percentiles by as much as 3%. Again, it appears that dominant incumbents preemptively reduce their low end fares earlier than non-dominant incumbents.

Table 4 Incumbent Responses To Entry By Entrant Type

VARIABLES *Origin Capacity Share*	(1) Ln(p80) < 0.15	(2) Ln(p20) < 0.15	(3) Ln(p80) > 0.25	(4) Ln(p20) > 0.25
LGC entry	-0.002	0.0006	-0.005	0.003
$t_0 - 3$	(0.005)	(0.004)	(0.004)	(0.003)
LGC entry	-0.019**	-0.015**	-0.014***	-0.004
$t_0 - 2$	(0.01)	(0.007)	(0.004)	(0.003)
LGC entry	-0.01	-0.021**	-0.018***	-0.01**
$t_0 - 1$	(0.01)	(0.008)	(0.005)	(0.004)
LGC entry	-0.007	-0.008	-0.007	-0.01*
t_0	(0.006)	(0.008)	(0.005)	(0.005)
LGC entry	-0.029***	-0.021***	-0.007	-0.005
$t_0 + 1$	(0.009)	(0.007)	(0.005)	(0.004)
LGC entry	-0.004	-0.012*	-0.01**	-0.009**
$t_0 + 2$	(0.005)	(0.007)	(0.004)	(0.003)
LCC entry	0.011	0.005	-0.003	-0.009*
$t_0 - 3$	(0.008)	(0.006)	(0.006)	(0.005)
LCC entry	-0.013	-0.012	-0.01	-0.014**
$t_0 - 2$	(0.01)	(0.01)	(0.007)	(0.005)
LCC entry	-0.03**	-0.028***	-0.02***	-0.014**
$t_0 - 1$	(0.01)	(0.01)	(0.007)	(0.005)
LCC entry	-0.02	-0.022**	-0.009	0.003
t_0	(0.01)	(0.01)	(0.009)	(0.006)
LCC entry	-0.044***	-0.032***	-0.026***	-0.013**
$t_0 + 1$	(0.01)	(0.01)	(0.008)	(0.005)
LCC entry	-0.024*	-0.014	-0.024***	-0.013**
$t_0 + 2$	(0.01)	(0.009)	(0.008)	(0.006)
Both entry	0.026*	0.027**	0.0005	0.002
$t_0 - 3$	(0.01)	(0.01)	(0.008)	(0.006)
Both entry	-0.012	-0.016	-0.01	-0.013*
$t_0 - 2$	(0.01)	(0.01)	(0.009)	(0.006)
Both entry	-0.051***	-0.047***	-0.03***	-0.017**
$t_0 - 1$	(0.01)	(0.01)	(0.01)	(0.007)
Both entry	-0.015	-0.014***	-0.014***	-0.017
t_0	(0.02)	(0.01)	(0.01)	(0.01)
Both entry	-0.055**	-0.038**	-0.023*	-0.003
$t_0 + 1$	(0.02)	(0.01)	(0.01)	(0.01)
Both entry	-0.039**	-0.028**	-0.021	-0.029***
$t_0 + 2$	(0.01)	(0.01)	(0.01)	(0.009)
Number of competitors	-0.035***	-0.025***	-0.0399***	-0.0182***
$t_0 - 1$	(.004)	(0.003)	(0.00472)	(0.00319)
Ln Enplaned passengers	-0.083***	-0.086***	-0.00376	-0.0341

Origin airport	(0.02)	(0.01)	(0.0209)	(0.0211)
Observations	32,443	32,443	23,196	23,196
R-squared	0.172	0.122	0.217	0.177
Number of carrier-routes	1,281	1,281	968	968

Notes. The dependent variable in columns (1) and (3) are the natural log of the 80th fare percentile for non-dominant and dominant incumbents respectively. The dependent variable in columns (2) and (4) are the natural log of the 20th fare percentile for non-dominant and dominant incumbents respectively. All incumbents are legacy airlines: American, Continental, Delta, Northwest, United and US Airways. Non-dominant incumbents are those with less than 15% capacity share (in terms of seat offerings) at the origin airport. Dominant incumbents are those with greater than 25% capacity share at the origin airport. All regressions include carrier-route and carrier-year-quarter fixed effects. The sample includes non-stop flights on 90% of the domestic routes served by these airlines. Entry is an indicator variable equal to one if entry of any kind occurred on route j in quarter t_0 and zero otherwise. The coefficients on Entry are interpreted as the effect of entry in quarter $t_0 \pm r$ compared to the excluded periods, quarters greater and less than $t_0 \pm r$. Robust standard errors are in parentheses and are clustered by carrier-route Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Secondary Results

The Role of FFP in the Heterogeneous Effects of Entry

While the primary results illustrate a more complete picture of the effect of entry on price dispersion, a secondary objective of this analysis is to differentiate the role of FFP from capacity share in the heterogeneous effect of entry. Purely descriptive work provided clear, albeit circumstantial, evidence that FFP may be an important factor in the ability of dominant airlines to preserve price dispersion in the face of increasing competition.

In order to determine whether these preliminary findings on FFP hold up to more rigorous examination equation **(4)** is re-estimated on only dominant incumbents**.** All observations of incumbents with less than 25% capacity share at the origin airport are dropped from the regression. Now, instead of comparing dominant and non-dominant airlines the model examines how the effect of entry on price dispersion varies across route types. As in the descriptive analysis, long-haul routes are compared to short-haul routes, and routes between two big cities are compared to routes with at least one endpoint that is not a big city. To restate the hypothesis, if FFP secure loyalty among elite status members then dominant incumbent's price dispersion should decrease more on short-haul routes and on routes not between two big cities.

Table 5 presents the estimates of equation **(4)** for Gini of dominant airlines on long-haul flights (greater than 1000 miles) and short-haul flights (less than 500 miles). It is immediately clear that there is small if any difference between the two. None of the estimates is statistically significant and the evidence that FFP are increasing incumbents' ability to price discriminate is very weak. Table 5 is included in the *Tables and Figures* section.

There is some evidence that LCC entry causes price dispersion to increase on long-haul routes and to decrease slightly on short-haul routes. Incumbent Gini on long-haul routes increases by as much as 0.004 while it decreases by as much as 0.002 on short-haul routes. Although imprecisely estimated, these coefficients are meaningfully different from each other. This is consistent, if not convincing, with the hypothesis that FFP help dominant airlines to price discriminate more effectively on long-haul routes. Additionally, *both* entry causes Gini to increase slightly, by 0.001 or less, on long-haul routes but causes it to decrease by as much 0.006 on short-haul routes. Again, although neither of these estimates is very large, they are meaningfully different from each other. This is, again, consistent with the hypothesis that FFP help dominant airlines to price discriminate more effectively on long-haul routes.

Table 6 presents the estimates of equation **(4)** for the Gini of dominant airlines comparing routes between two large cities and all other routes. Again, few of the estimates are statistically significant. There is some evidence that LCC entry causes price dispersion to increase more on routes between big cities. This could be interpreted as weak evidence that FFP are helping dominant airlines price discriminate when LCC entry occurs. LGC entry and *both* entry are found to decrease price dispersion *more* on routes between two big cities. This contradicts the hypothesis that FFP help dominant airlines to price discriminate more effectively on routes between big cities. Also, it contradicts the early descriptive findings. This is surprising given the strength of the descriptive indications that dominant carriers preserve price dispersion very well on big city routes. Table 6 is included in the *Tables and Figures* section.

Additional Specifications

In an attempt to offer insight and additional clarity to the primary results in this paper some additional analyses are performed. A common critique of event studies and fixed effects models, like the one employed here, is that they fail to appropriately address the endogeneity of key independent variables. In this paper, there is legitimate concern that the event study framework with carrier-route fixed effects and carrier-quarter fixed effects does not sufficiently address the endogeneity of route entry and airfares. An airline almost certainly selects which routes to enter based partially on incumbents' airfares, and any number of demand factors related to both the fares currently charged by incumbent airlines, and the fares an entrant can expect to charge after entry. This creates potential selection bias whereby, the parameter estimates of entry on price dispersion and fare percentiles, are likely to be biased.

The estimates are likely biased towards zero if airlines choose to enter routes with unobserved demand characteristics that are positively correlated with price or inelastic consumer behavior. This is because unobserved demand characteristics, which are positively correlated with both price and entry, are then included in the error term. The selection of new routes by airlines where demand factors make fares relatively insensitive to competition, result in parameter estimates that underestimate the true effect of entry on price dispersion or price percentiles.

Two alternate specifications are estimated in an attempt to minimize the concern of selection bias. First, a control function is estimated; this specification is equivalent to a multivariate regression. In a control function, a host of variables correlated with route-specific demand and cost of entry are added to the regression. The assumption is that, after controlling for all factors that explain demand and cost, remaining variation in entry is exogenous. The limitation of this approach is, of course, the difficulty involved in being able to identify and observe all factors associated with demand and the cost of entry on a route. Potential variables of interest in the current data set include the percent of tickets bought online, the number of passengers at the origin airport, the number of passengers at the destination airport, average load factor, the percent of tickets which are round trip, the number of direct flights from the origin airport, and a dummy variable for 2001, which accounts for the disruption to demand caused by terrorist attacks. The number of enplaned passengers at the origin airport, which was used in this paper's preferred specifications as an independent variable, is still included.

Additional variables associated with demand that do not change over time but are likely to be correlated with either demand or cost of entry are whether an airport is slot controlled, and whether it is a popular leisure destination such as Florida, Las Vegas or Hawaii. Also, the route distance is likely to be correlated with demand. The relationship is likely increasing with distance and non-linear since, for short distances, viable substitutes such as car, bus or train are more likely to exist. Long distances have fewer substitutes so demand for flights is higher but consumers' also have a disutility for long travel time; at some distance demand for flights likely decreases. Unfortunately, since distance, distance squared and these other route variables do not change over time, they cannot be included in a model with carrier-route fixed effects. On the other hand, they could be included in a control function that does not include route fixed effects.

An event study with carrier-route fixed effects, carrier-quarter fixed effects, LCC and LGC entry, and the complete set of controls is estimated. As before, the event study estimation equation includes the full set of time dummy variables; starting three years before entry and ending a full year after entry. Abbreviated results are shown in Table 7 below.

Table 7 Control Function Parameter Estimates

VARIABLES	Ln(Gini)	Ln(p80)	Ln(p20)	Ln(mean)
LGC entry	-0.013***	-0.013***	0.002	-0.007**
	(0.002)	(0.004)	(0.003)	(0.003)
LCC entry	-0.0058	-0.008	-0.017***	-0.019***
	(0.004)	(0.007)	(0.005)	(0.005)
percent_online	0.021***	0.16	0.117***	-0.05***
	(0.003)	(0.006)	(0.004)	(0.005)
Ln(Pssngrs on the route)	-0.015***	-0.09***	-0.07***	-0.08***
	(0.003)	(0.006)	(0.004)	(0.004)
Ln(Pssngrs at origin airport)	-0.042***	-0.067***	-0.05***	-0.017*
	(0.007)	(0.01)	(0.01)	(0.01)
Ln(Pssngrs at destination airport)	-0.0012	-0.009***	-0.005***	-0.007***
	(0.0015)	(0.0027)	(0.001)	(0.002)
Ln(Load factor)	-0.066***	-0.34***	-0.17***	-0.13***
	(0.008)	(0.01)	(0.01)	(0.01)
Percent round trip	-0.011	-0.039*	0.14***	0.21***
	(0.01)	(0.02)	(0.017)	(0.017)
Dummy_2001	0.087***	0.05***	-0.02***	0.05***
	(0.003)	(0.006)	(0.004)	(0.005)
Ln(Num. of direct flights	-0.25***	-0.16***	0.023**	-0.22***
from origin airport)	(0.008)	(0.016)	(0.01)	(0.01)
Observations	15,809	15,809	15,809	15,786
Number of routes	553	553	553	550
F(58, 15,198)	20.61	40.96	30.16	52.4
Prob > F	0.00	0.00	0.00	0.00

Dependent variables are the natural log of the Gini coefficient of price dispersion, the 80th price percentile, the 20th price percentile and mean price (in 2010 dollars). LGC entry is a dummy for the entry of a legacy carrier, LCC entry is a dummy for the entry of a low cost carrier

The control function predicts a 1.3% decrease in price dispersion for LGC entry and a roughly 0.5% decrease in price dispersion for LCC entry. Only the effect of LGC entry is statistically significant. The contraction in price dispersion seems to be driven by a large, statistically significant decrease in the 80th price percentile associated with LCC entry. LCC entry has a slightly larger and statistically significant effect on average price. The effect is economically small, however, reducing average price only about 2%. The control variables are nearly all statistically significant, although the signs are not always intuitive. The control function is run for carriers falling into different buckets of origin airport capacity share; those with less than 25%, 25-50%, and greater than 50%. The estimated effects of entry are virtually identical.

In a second attempt to deal with the endogeneity of entry and price, a 2SLS is run with several instruments for entry. The instruments used are dummy variables for whether an airline currently operates at both endpoint airports, distance and distance squared. The assumption is that it is much less costly for an airline to begin offering flights on a new route when it already operates at both endpoints. The increased likelihood of Southwest to enter on routes where it operated in both airports is demonstrated in detail in Goolsbee and Syverson (2008).

In order for the operation of an airline at both endpoints to be a valid instrument for entry it must satisfy the exclusion restriction. When an airline chooses whether to enter a route between airports where it already operates or a similar route where it does not, the presence of the airline at both airports or not must capture a fundamental difference in the fixed cost of entry. It must also be orthogonal to the variable costs associated with flying the route. This is because, after entry occurs, demand, variable cost, competition and other fundamental market conditions all play a role in determining fares. Alternatively, fixed costs play an important role in the decision whether or not to enter a route but do not affect pricing decisions after entry.

When an airline's decision to enter a route also entails beginning operations at a new airport it likely requires the drafting of new contracts with municipal governments that run the airports and other agencies providing necessary services such as security, fueling, baggage handling etc. Also, it may require airlines to hire employees at the new location. Conversely, entering a route between airports where an airline already operates is more likely to require a reallocation of labor and capital. In this way, operating at both airports captures the difference in airport set up costs. This instrument could fail to pass the exclusion restriction if, for example, operating at both airports captures economies of scale that reduce the operating costs of a flight itself. Operating at both endpoints would thus affect fares through both its effect on entry and its effect on cost. If this is the case then instrumenting for entry with an airline's presence at both endpoint airports will produce biased estimates.

This specification still includes the complete set of control variables, carrier-route fixed effects, carrier-quarter fixed effects and the event study time dummies around entry. Instruments of whether an airline exists at both endpoint airports of a route, in a given quarter, are constructed for each airline included in the sample. The first stage is displayed in Table 8 below.

The instruments are mostly individually statistically significant with intuitive signs. Legacy carriers in both endpoints are positively correlated with LGC entry and negatively correlated LCC entry. Low cost carriers in both endpoints are positively correlated with LCC entry and negatively correlated with LGC entry.

Unfortunately, it should also be noted that F-statistics are below 10 which is sometimes used as an indicator of a potential weak instrument problem.

Table 8 FIRST STAGE REGRESSION

VARIABLES	(1) LGC entry	(2) LCC entry
Distance	0.09	-0.02
(1000m)	(0.3)	(0.1)
Distance^2	-5.67e-05	-4.19e-06
(1000m)	(1.69e-07)	(9.86e-08)
UA in both	0.076***	-0.018**
	(0.01)	(0.009)
AA in both	0.08***	-0.0019
	(0.02)	(0.01)
CO in both	0.083***	-0.023***
	(0.01)	(0.008)
DL in both	0.014	-0.005
	(0.02)	(0.01)
NW in both	-0.081***	0.072***
	(0.01)	(0.009)
US in both	0.09***	-0.014**
	(0.013)	(0.007)
HA in both	0.04*	-0.019
	(0.02)	(0.01)
AS in both	0.048***	-0.018***
	(0.01)	(0.007)
SW in both	-0.028*	-0.0018
	(0.01)	(0.009)
JB in both	-0.02	-0.0013
	(0.03)	(0.01)
FR in both	-0.02*	0.02***
	(0.01)	(0.006)
Observations	15,786	15,786
Number of routes	550	550
F(129, 47574)	11.68	9.55
Prob > F =	0.00	0.00

LGC: UA = United, AA = American, CO = Continental, DL = Delta, NW = Northwest, US = US Airways, HA = Hawaiian Airways, AS = Alaskan Airways. LCC: SW = Southwest, JB = Jet Blue and FR = Frontier

Abbreviated second stage results are shown here in Table 9.

Table 9 2SLS Parameter Estimates

VARIABLES	Ln(Gini)	Ln(p80)	Ln(p20)	Ln(mean)
LGC entry	-0.18***	-0.04	-0.059	-0.10**
	(0.03)	(0.06)	(0.048)	(0.05)
LCC entry	-0.26**	-0.68***	-0.59***	-0.68***
	(0.11)	(0.20)	(0.15)	(0.16)
Ln(percent_online)	0.023***	0.17***	0.12***	0.14***
	(0.004)	(0.008)	(0.006)	(0.007)
Ln(Pssngrs on the route)	-0.015***	-0.09***	-0.069***	-0.078***
	(0.003)	(0.007)	(0.0057)	(0.006)
Ln(Pssngrs at origin airport)	-0.04***	-0.06***	-0.051***	-0.073***
	(0.01)	(0.018)	(0.01)	(0.015)
Ln(Pssngrs at dest. airport)	-0.0019	-0.0097***	-0.005**	-0.008***
	(0.001)	(0.003)	(0.002)	(0.002)
Ln(Load factor)	-0.04***	-0.30***	-0.14***	-0.22***
	(0.01)	(0.02)	(0.017)	(0.018)
Dummy_2001	0.07***	0.05***	-0.024***	0.04***
	(0.004)	(0.008)	(0.006)	(0.007)
Observations	15,786	15,786	15,786	15,786
Number of routes	550	550	550	550
Wald Chi^2(116)	9.41e+05	7.11e+06	1.95e+07	9.31e+06
Prob > chi^2	0.00	0.00	0.00	0.00

Dependent variables are the natural log of the Gini coefficient of price dispersion, the 80th price percentile, the 20th price percentile and mean price (in 2010 dollars). LGC entry is a dummy for the entry of a legacy carrier, LCC entry is a dummy for the entry of a low cost carrier

The change in the effect of entry is dramatic. LGC entry decreases price dispersion by 18% and LCC entry decreases price dispersion by 26% and both are statistically significant. LCC entry is associated with large, statistically significant decreases in both the 80th and 20th price percentiles. LGC is associated with a 10%, statistically significant decrease in average price while LCC is associated with a 68% statistically significant decrease in average price. These findings are not dissimilar from a number of studies that find large and significant price decreases associated with the entry of Southwest. In particular a number of studies find the negative effect of Southwest's entry on average price to be greater than 50% of average price [Windle and Dresner (1995); Vowles (2000); Windle and Dresner (1998)]. As a final check this regression is rerun excluding distance from the first stage. In particular, there is concern that since distance flown is correlated with variable costs it should not be used as an instrument for entry. The 2nd stage results are presented in Table 11 in the *Tables and Figures* section.

Similar to the other model specifications, the 2SLS regression is run for carriers falling into different buckets of origin airport capacity share; those with less than 25%, 25-50%, greater than 50% and greater than 75%. No significant differences in the effect of entry are found by airline's origin airport capacity share except in the extreme cases where an airline has greater than 75% share. These results, shown in Table 10 below, find a positive but statistically insignificant relationship between entry and price dispersion. It appears to be driven by the fact that the 20th price percentile is decreasing more than the 80th price percentile with entry, although again, the estimates are not statistically significant.

Table 10 2SLS for Incumbent Airlines with > 75% Capacity Share at the Origin Airport

VARIABLES	Ln(Gini)	Ln(p80)	Ln(p20)	Ln(mean)
LGC entry	0.08	-0.0013	-0.12	-0.039
	(0.06)	(0.09)	(0.086)	(0.063)
LCC entry	0.23	-0.07	-0.119	-0.125
	(0.14)	(0.22)	(0.20)	(0.14)
Ln(percent_online)	-0.022	-0.14	-0.32**	-0.12
	(0.11)	(0.17)	(0.15)	(0.11)
Observations	936	936	936	936
Number of routes	133	133	133	133
Wald Chi^2(116)	9.41e+05	1.48e+06	1.20e+06	2.94e+06

Conclusions

This paper has examined the effect of competition on airline fare dispersion in a way that reconciles and expands upon previous studies. Acknowledging, as others have, the problems with cross-sectional analysis and the endogeneity of fares and entry the models have predominantly relied on panel data, extensive fixed effects and a flexible, event study modeling framework in order to glean new insight. Also, it has attempted to use a control function and instrumental variables in additional specifications in order to better control for the endogeneity of entry.

The primary results indicate that the effects of entry on price dispersion are indeed heterogeneous. Increased incumbent market power is associated with greater degrees of insulation from competition. A non-dominant incumbent's fare dispersion decreases as much as ten times more than that of a dominant incumbent. There is weak evidence that the superiority of a dominant incumbent's FFP is at least partially responsible for this result. Imprecise point estimates also indicate that fare dispersion may be increasing when incumbents have very large market power (airport capacity share greater than 50%) or when the entrant is a low cost carrier.

The additional specifications find less evidence of a heterogeneous effect. Increased capacity share at the origin airport does not appear to be correlated with the magnitude of the estimates of the coefficients on entry in either the control function or 2SLS. There is some evidence that price dispersion increases with entry for incumbents with greater than 70% capacity share in the 2SLS model, although the estimates are not statistically significant. Findings in the control function are not meaningfully different from the primary results. The effect of entry in the 2SLS regression is much larger in magnitude than the primary estimates and statistically significant. The 2SLS indicate that bias due to the endogeneity of entry is probably large.

In line with a previous study by Goolsbee and Syverson (2008) there is also consistent evidence that airlines take preemptive action when competitors announce their intent to enter a route. Suggestive evidence favors the explanation that these actions are taken to deter entry although it is far from conclusive.

Finally, this paper argues that recent attempts to measure the effect of entry on fare dispersion using instrumental variables correlated with demand have significantly overestimated the negative impact of competition. It is further argued that these studies have relied on rigid assumptions and only focused, too narrowly, on the period of entry. The aspiration of this paper was reconcile some of the contradictory findings with a more flexible model and to expand upon the existing understandings with the use of a different approach.

One surprising result of this study was the apparent importance of the entry of a legacy and a low cost carrier occurring within close proximity to each other. The impact of *both* entry appears to have a more significant impact on price dispersion even, than simultaneous entry of multiple LGCs or multiple LCCs. While the incidence of routes experiencing *both* entry is small, it is not insignificant.

Approximately 6% of carrier-route observations in the panel experienced *both* entry. The magnitude of the effect of *both* entry could be due to selection, the types of routes both LGC and LCC enter, or perhaps an inability of incumbents to respond optimally to the simultaneous entry of different carrier types. This could be an interesting topic for future empirical research.

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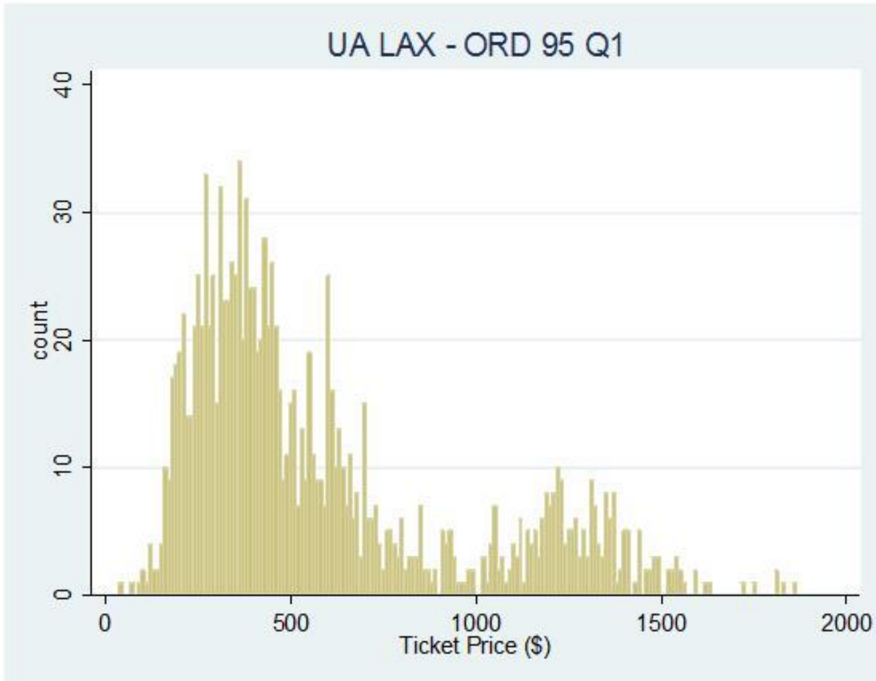
Additional Tables and Figures

Histogram 1



Histogram of United airfares between Los Angeles (LAX) and Chicago O'Hare (ORD) in the first quarter of 1995.

Figure 1 continued 1

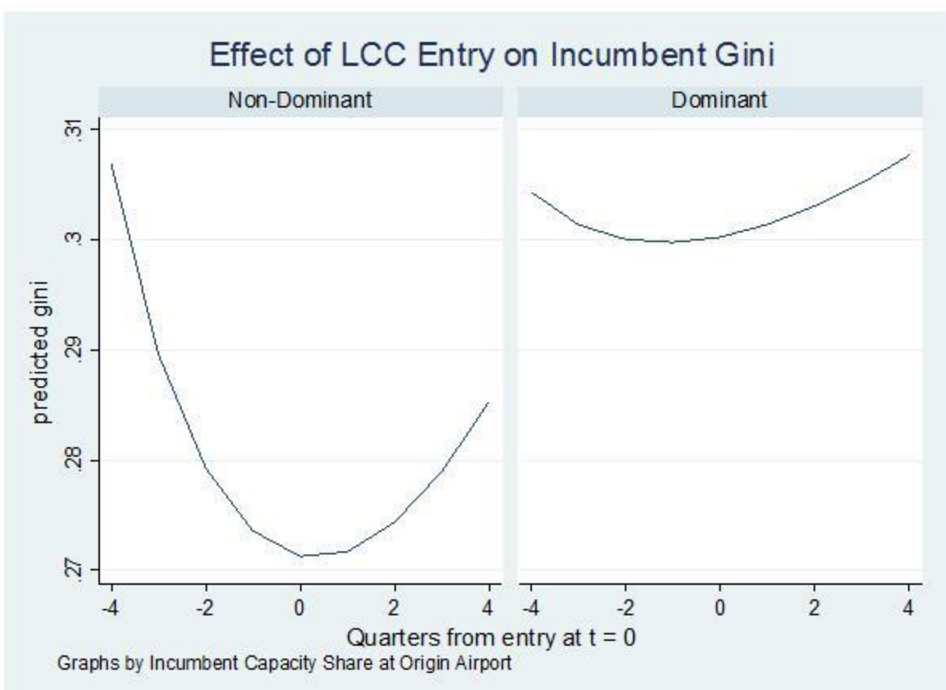


Figure 1 continued 2

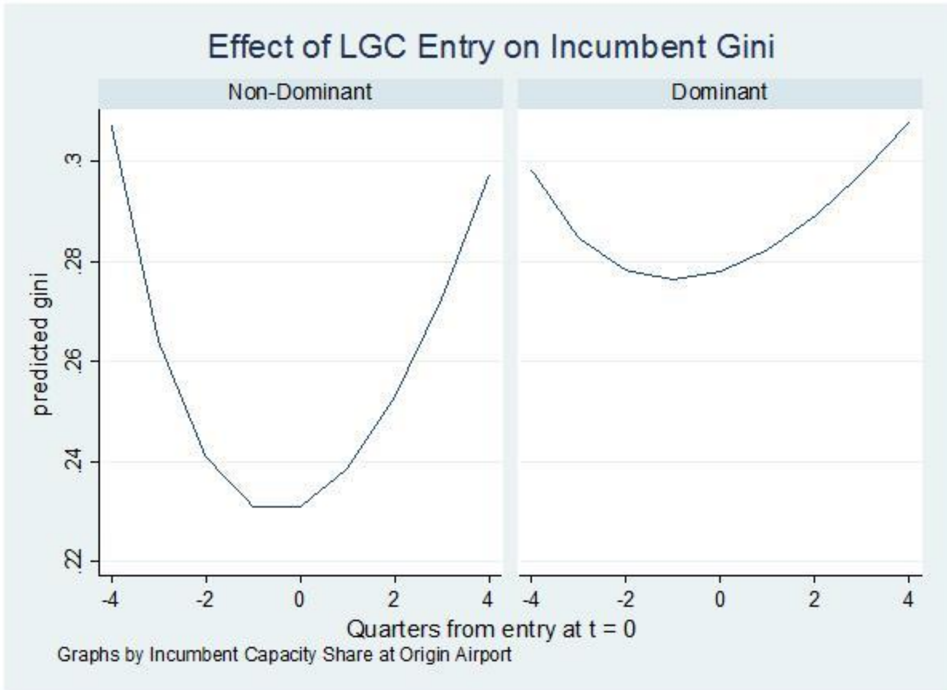


Figure 1 continued 3

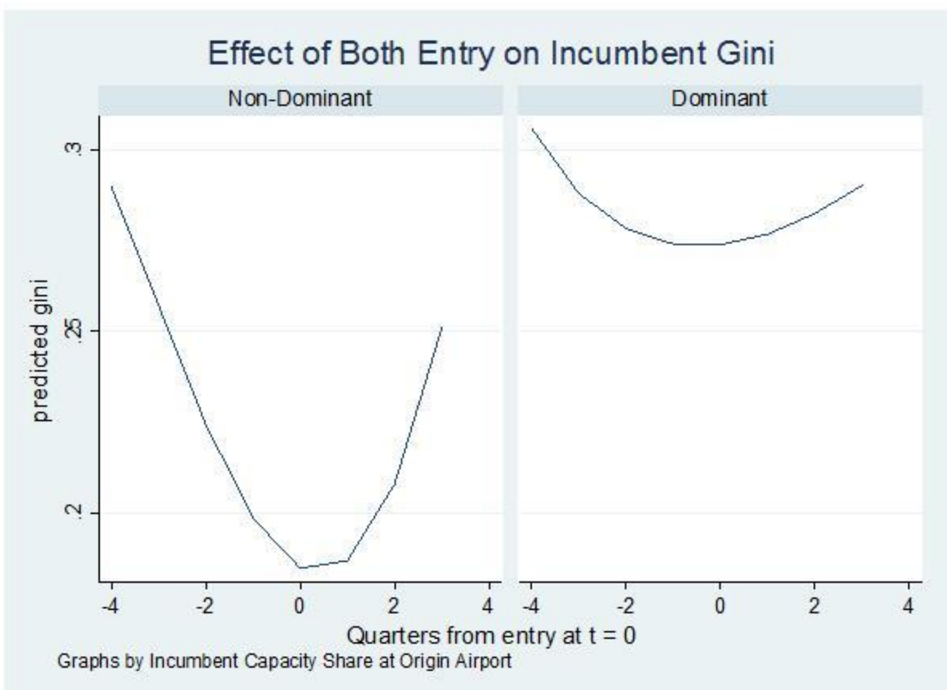


Table 5 DOMINANT INCUMBENT RESPONSES BY ROUTE Distance

VARIABLES *Route distance (miles)*	(1) Gini > 1000	(2) Gini < 500
LGC entry	0.001	0.0005
t_0 - 2	(0.001)	(0.001)
LGC entry	-0.0006	0.001
t_0 - 1	(0.001)	(0.001)
LGC entry	0.0003	-0.0003
t_0	(0.001)	(0.001)
LGC entry	-0.003*	0.001
t_0 + 1	(0.001)	(0.001)
LGC entry	0.001	0.001
t_0 + 2	(0.001)	(0.001)
LCC entry	0.003	0.001
t_0 - 2	(0.002)	(0.002)
LCC entry	0.0001	0.001
t_0 - 1	(0.002)	(0.002)
LCC entry	0.002	0.001
t_0	(0.002)	(0.002)
LCC entry	0.003	-0.001
t_0 + 1	(0.002)	(0.002)
LCC entry	0.004*	-0.002
t_0 + 2	(0.002)	(0.002)
Both entry	0.006	-0.0003
t_0 - 2	(0.004)	(0.002)
Both entry	0.005	-0.001
t_0 - 1	(0.004)	(0.002)
Both entry	0.001	-0.004
t_0	(0.003)	(0.003)
Both entry	-0.001	-0.005
t_0 + 1	(0.004)	(0.003)
Both entry	0.0003	-0.006
t_0 + 2	(0.004)	(0.003)
Observations	6,413	11,559
R-squared	0.406	0.290
Number of carrier-routes	333	574

Notes. The dependent variable in columns (1) and (2) is the Gini coefficient of fare dispersion for legacy airlines: American, Continental, Delta, Northwest, United and US Airways. Only observations of dominant incumbents are included in the regression. Dominant incumbents are defined as those with greater than 25% capacity share at the origin airport. The columns are divided into long-haul and short-haul routes. All routes between 500 and 1000 miles are excluded. Both regressions include carrier-route and carrier-year-quarter fixed effects. The sample includes non-stop flights on 90% of the domestic routes served by these airlines. Entry is an indicator variable equal to one if entry of any kind occurred on route *j* in quarter t_0 and zero otherwise. The coefficients on Entry are interpreted as the effect of entry in quarter $t_0 \pm r$ compared to the excluded periods, quarters greater and less than $t_0 \pm r$. Robust standard errors are in parentheses and are clustered by carrier-route *** p<0.01, ** p<0.05, * p<0.1

Table 6 DOMINANT INCUMBENT RESPONSES BY ROUTE Type

VARIABLES	(1) Gini	(2) Gini
Route type	Btw big cities	All other
LGC entry	-0.002	0.001
t_0 - 2	(0.002)	(0.0008)
LGC entry	-0.002	0.001
t_0 - 1	(0.002)	(0.0008)
LGC entry	0.001	0.0001
t_0	(0.002)	(0.0008)
LGC entry	-0.004*	0.001
t_0 + 1	(0.002)	(0.0008)
LGC entry	-0.004*	0.001
t_0 + 2	(0.002)	(0.0008)
LCC entry	0.0003	0.003**
t_0 - 2	(0.002)	(0.001)
LCC entry	0.002	0.003*
t_0 - 1	(0.002)	(0.001)
LCC entry	0.006*	0.002
t_0	(0.003)	(0.001)
LCC entry	0.001	0.002
t_0 + 1	(0.003)	(0.001)
LCC entry	0.0001	0.002
t_0 + 2	(0.002)	(0.001)
Both entry	-0.004	0.005**
t_0 - 2	(0.003)	(0.002)
Both entry	-0.002	0.005**
t_0 - 1	(0.003)	(0.002)
Both entry	-0.004	-0.0003
t_0	(0.004)	(0.002)
Both entry	-0.006	0.0005
t_0 + 1	(0.003)	(0.002)
Both entry	-0.007*	0.001
t_0 + 2	(0.003)	(0.002)
Observations	1,760	25,765
R-squared	0.642	0.275
Number of carrier-routes	78	1,133

Notes. The dependent variable in columns (1) and (2) is the Gini coefficient of fare dispersion for legacy airlines: American, Continental, Delta, Northwest, United and US Airways. Only observations of dominant incumbents are included in the regression. Dominant incumbents are defined as those with greater than 25% capacity share at the origin airport. The columns are divided into big city and all other routes. Big city routes are routes between any of the 10 largest cities by enplaned passengers at the city airport(s). In no particular order these are Houston, Miami, Denver, Washington DC, San Francisco, Los Angeles, Dallas, New York, Atlanta and Chicago. Both regressions include carrier-route and carrier-year-quarter fixed effects. The sample includes non-stop flights on 90% of the domestic routes served by these airlines. Entry is an indicator variable equal to one if entry of any kind occurred on route *j* in quarter t_0 and zero otherwise. The coefficients on Entry are interpreted as the effect of entry in quarter $t_0 \pm r$ compared to the excluded periods, quarters greater and less than $t_0 \pm r$. Robust standard errors are in parentheses and are clustered by carrier-route *** p<0.01, ** p<0.05, * p<0.1

Table 11 2^{nd} Stage of 2SLS Estimation Excluding Distance from the First stage

VARIABLES	Ln(Gini)	Ln(p80)	Ln(p20)	Ln(mean)
LGC entry	-0.20***	-0.09	-0.03	-0.09**
	(0.04)	(0.06)	(0.057)	(0.04)
LCC entry	-0.32***	-0.54***	-0.41***	-0.59***
	(0.10)	(0.16)	(0.14)	(0.11)
Observations	16,439	16,450	16,450	15,786
Number of routes	592	592	592	550
Wald Chi^2(116)	8.1e+05	8.5e+06	7.66e+07	9.31e+06
Prob > chi^2	0.00	0.00	0.00	0.00

Dependent variables are the natural log of the Gini coefficient of price dispersion, the 80^{th} price percentile, the 20^{th} price percentile and mean price (in 2010 dollars). LGC entry is a dummy for the entry of a legacy carrier, LCC entry is a dummy for the entry of a low cost carrier

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