Estimating Machinery Supply Elasticities Using Output Price Booms

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October 28, 2009

Abstract

Recent years have seen large movements in the prices of houses, farm products, metals, and oil. These movements created plausibly exogenous shifts in demand for construction, farm, and mining machinery. This paper uses these shifts in demand to estimate the elasticity of machinery supply. Graphical evidence, OLS, and IV estimates all indicate that the quantity of machinery supplied increased rapidly during the booms, with only modest increases in prices. Pooled sample estimates of the supply elasticity are around 5, much larger than the estimate of 1 from Goolsbee [1998]. Results thus suggest that public policies that stimulate investment demand will have only modest effects on the prices of investment goods.

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1 Introduction

The price elasticity of the supply of investment goods is a key parameter determining the impact and incidence of public policies intended to stimulate business investment. Many seminal papers have implicitly or explicitly assumed that the supply of investment goods is perfectly elastic—that is, that the supply of investment goods can increase to satisfy any increase in demand without an increase in prices. Hall and Jorgenson [1967] and Summers [1981], for example, study the impact of tax policy on investment decisions under the assumption that any amount of physical capital can be purchased at a fixed price.

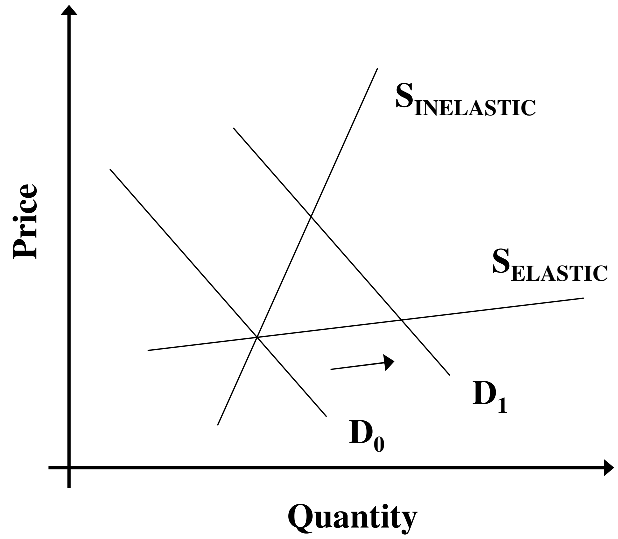
Goolsbee [1998], however, pointed out that the supply curve of investment goods may be upward sloping.[1] In the short run, policies designed to stimulate demand for investment goods might increase the prices of these goods. This increase would tend to mitigate the impact of such policies on real investment quantities, and it would tend to benefit suppliers of these goods at the expense of purchasers. Goolsbee [1998] estimated that this was, in fact, the case. He found a supply elasticity around 1, and he estimated that a 10% investment tax credit would increase the prices of investment goods by 5.6%. Figure 1 illustrates the effects of a positive demand shock on prices and quantities with elastic and inelastic supply curves.

This paper provides new evidence on the supply elasticity of investment goods by exploiting recent large movements in the prices of many commodities. Over the last several years, the prices of houses, farm products, metals, and oil rose to astounding heights before crashing before and during the financial crisis. The case of housing is particularly familiar, and consensus opinion seems to be that these high prices resulted from a speculative bubble with little relation to economic fundamentals.[2] Researchers have struggled to explain the

[1] Some economists prefer the term "supply relationship" to reflect the fact that a demand-invariant relationship between price and the quantity supplied need not exist when markets are not perfectly competitive. Results in the paper do not depend on the assumption of competitive markets, but I use the familiar term "supply curve" anyway.

[2] For example, Robert Solow wrote in the *New York Review of Books*, "The word "bubble" is often misused; but there was a housing bubble. Rising house prices induced many people to buy houses simply because they expected prices to rise; those purchases drove prices still higher, and confirmed the expectation.

Figure 1: Effects of a Positive Demand Shock with Elastic and Inelastic Supply Curves



With an elastic supply curve, a positive demand shock produces a large increase in quantity and a small increase in price. With an inelastic supply curve, it produces a small increase in quantity and a large increase in price.

rise in food prices, with some claiming increased demand from worldwide biofuel production as the most important factor (Mitchell [2008]). Hamilton [2008] sees growth in demand from China and other newly industrialized countries as a factor in recent oil price increases, but concedes that, "The \$140/barrel price in the summer of 2008 and the \$60/barrel in November of 2008 could not both be consistent with the same calculation of a scarcity rent warranted by long-term fundamentals." Thus it seems that much of the recent run-ups in goods prices may have had little relation to economic fundamentals. At the very least, price increases were driven by demand shocks and not by shocks to the supply of machinery used to produce these goods.

These price increases did, however, lead to increased demand for this construction, farm, and mining machinery. This paper uses these demand shifts to estimate machinery supply curves. Textbook simultaneous equations models demonstrate that exogenous shifts in demand can be used to identify supply curves (or vice versa). If the only variation in the data

Prices rose because they had been rising."

comes from demand shifts, then ordinary least squares will correctly estimate the supply curve. If there are also supply shocks in the data, then instrumental variables estimates exploiting an exogenous demand shifter can still correctly estimate the supply curve. I show in this familiar setting that OLS "forward" regressions of quantity on price produce an upward-biased estimate of the supply elasticity when supply and demand shocks are uncorrelated, while OLS "reverse" regressions of price on quantity produce a downward-biased estimate of the supply elasticity.[3] I argue that the most plausible story for a correlation between demand and supply shocks would tend to bias results towards lower elasticity estimates.

Graphical evidence, OLS estimates, and instrumental variables estimates all tell similar stories. The price elasticity of construction machinery supply is quite large—at least 10—while the supply elasticities of farm machinery and mining machinery are around 2 and 5. Pooling the sample and weighting by each type of machinery's share of aggregate investment produces supply elasticity estimates around 5. Even if the machinery demand elasticity were as large as 1 in absolute value, these estimates would suggest that only 17%, or 1/(1+5), of the value of tax incentives for invesment would be passed into machinery prices.[4] It is likely that increasing globalization of the machinery market has contributed to the flattening of supply curves since the period studied by Goolsbee [1998].

This paper is similar in spirit to Shea [1993], who uses "approximately exogenous" demand shocks to estimate supply curves for many industries. He finds upward-sloping supply curves for many consumer and intermediate goods industries, but downward-sloping supply curves for construction machinery and aircraft. These latter results contrast with Goolsbee's. This paper differs from Shea [1993] in its focus on recent periods where the presence of large demand shocks is particularly clear, in its focus on transparent, graphical presentation of results, and in the sign of its main result. Other related papers include Hassett and Hubbard [1998] and Whelan [1999], which question the robustness of Goolsbee's results. Sallee [2009]

[3]This has undoubtedly been shown before, but I have not yet located a reference.

[4]This calculation uses the approximation that the share $-\eta_d/(\eta_s - \eta_d)$ of a small subsidy is passed to suppliers in a competitive market, for η_d the elasticity of demand and η_s the elasticity of supply.

finds that tax incentives for the purchase of hybrid cars had no effect on Toyota Prius prices, even though Prius supply was quite inelastic.

The following section of the paper reviews the estimation of supply curves in a simultaneous equations setting. Section 3 discusses and describes the data. Section 4 presents results, and Section 5 concludes.

2 The simultaneous equations model

Suppose price and quantity data are generated by the sytem of equations,

$$q = \beta p + \epsilon_s \tag{1}$$

$$q = \gamma_1 p + \gamma_2 z + \epsilon_d \tag{2}$$

$$p = \pi z + \nu, \tag{3}$$

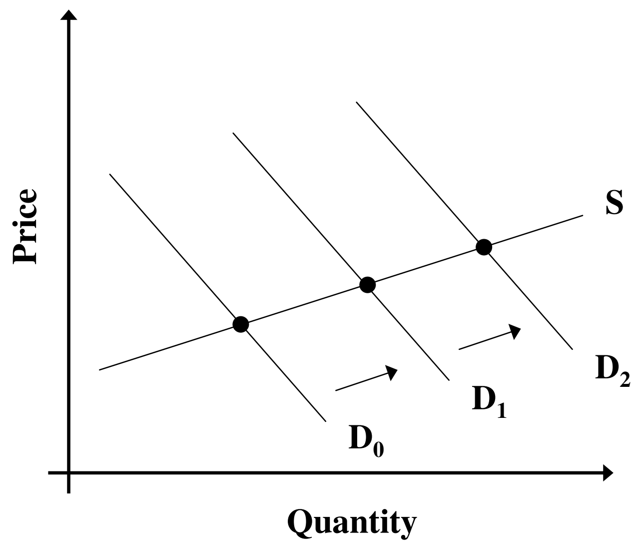
where p and q are logarithms of prices and quantities, and constants and any other exogenous variables are partialled out. Equations (1) and (2) are the "structural" supply and demand equations, in the language of Hausman [1983]. The supply elasticity β is the parameter of interest. The exogenous demand shifter z enters only the demand equation and not the supply equation. Equation (3) relating p and z is a "reduced form" equation in the language of Hausman [1983], but is commonly referred to as the "first stage" of two-stage least squares (2SLS) estimation of equation (1).

Recall that asymptotic bias in the OLS estimate of β depends on the correlation of p and the supply shocks ϵ_s,

$$\text{plim } \hat{\beta}_{OLS} = \beta + \frac{cov(\epsilon_s, p)}{var(p)}.$$

If we could examine data from a period with no supply shocks ($\epsilon_s = 0$), then an OLS regression of q on p would correctly estimate the supply elasticity. If instead we have data from a period where demand shocks are large relative to suppy shocks, there would be large

Figure 2: Demand Shocks Tracing Out the Supply Curve



demand-induced changes in p, with only small changes in ϵ_s. The numerator of the bias term is small, while the denominator is large, and OLS will not be badly biased. I claim that recent run-ups in commodity prices have created this kind of variation in the data. There were large shocks to demand that likely swamp any shocks to supply. Simple OLS regressions using data from the commodity price boom periods will probably not produce badly biased supply elasticity estimates. Figure 2 depicts a situation like this graphically.

It can be shown that the bias term can be written,

$$\frac{cov(\epsilon_s, p)}{var(p)} = \frac{var(\epsilon_s) - cov(\epsilon_s, (\gamma_2 z + \epsilon_d))}{(\gamma_1 - \beta)var(p)}.$$

If we are willing to assume that supply shocks are uncorrelated with demand shocks ($cov(\epsilon_s, (\gamma_2 z + \epsilon_d)) = 0$), then we can sign the OLS bias. Assuming that demand curves slope down ($\gamma_1 < 0$) and supply curves slope up ($\beta > 0$), the OLS estimate of β will be downward biased.

Next, consider the "reverse" supply equation relating prices to quantities,

$$p = \frac{1}{\beta} q - \frac{\epsilon_s}{\beta}.$$

Denote $c = (1/\beta)$, and note that $1/\hat{c}$ is a potential estimator for β, with,

$$\text{plim } \hat{c}_{OLS} = \frac{1}{\beta} + \frac{cov(-\epsilon_s/\beta, q)}{var(q)} = \frac{1}{\beta} - \frac{cov(\epsilon_s, q)}{\beta var(q)}.$$

It can be shown that this bias term can be written,

$$\frac{cov(\epsilon_s, q)}{\beta var(q)} = \frac{\frac{\gamma_1}{\beta} var(\epsilon_s) - cov(\epsilon_s, (\gamma_2 z + \epsilon_d))}{(\gamma_1 - \beta) var(q)}$$

These results are derived in an appendix. Under the same assumptions ($cov(\epsilon_s, (\gamma_2 z + \epsilon_d)) = 0$, $\gamma_1 < 0$, and $\beta > 0$), we see that $\hat{c}$ is biased downwards, and thus that $1/\hat{c}$ is biased *upwards* as an estimator of β. Because $\hat{\beta}_{OLS}$ was biased *downwards*, the two estimators could be used to estimate upper and lower bounds on β. It is well-known that the product $\hat{\beta}_{OLS} \times \hat{c}_{OLS}$ must equal the R^2, which is equal in both regressions. Thus the two estimates can provide tight bounds when the R^2 is high, but only loose bounds when it is low.

Of course, the two-stage least squares (2SLS) estimator may also be available, with,

$$\text{plim } \hat{\beta}_{2SLS} = \beta + \frac{cov(\epsilon_s, z)}{cov(p, z)}.$$

It is thus a consistent estimator of β whenever $cov(\epsilon_s, z) = 0$. When instruments are valid and supply and demand shocks are not badly correlated, we should see that forward and reverse OLS and 2SLS estimates are all close together. When multiple instrumental variables are available, Hahn and Hausman [2002] provide a formal specification test based on the notion that forward and reverse 2SLS estimates should also be close together.

It is worth considering what will happen if instruments are invalid. The denominator of the 2SLS bias term will be positive as long as favorable supply shocks are not so highly correlated with the instrument that p and z are negatively correlated, which, we will see, is clearly not the case in the data used in this paper. Thus the sign of the bias will be determined by the term $cov(\epsilon_s, z)$. In this paper, z represents the prices of houses, farm products, and oil. I have argued that much of the variation in z in recent years has been driven by speculative bubbles and demand shocks, rather than machinery supply shocks.

Nonetheless, plausible stories for correlation between ϵ_s and z may exist. I find the most plausible story to be the following. Global demand or a housing bubble drove up aggregate demand in the United States, increasing wages and other costs involved in machinery production. There would thus be a correlation between strong demand for machinery and unfavorable machinery supply shocks, which entails a negative correlation between z and ϵ_s. In this setting, my estimates of the supply elasticity would be biased downward. As I claim to find *large* estimates of the supply elasticity, this bias "works against me."

Another story might be the following. Exogenous increases in the price of oil hurt the economy, driving down wages and other machinery production costs. There would thus be a correlation between strong demand for oil and favorable supply shocks in machinery manufacturing, which entails a positive correlation between z and ϵ_s and an upward bias in supply elasticity estimates. In response, I would say first that this story is most plausible for oil, as the relationship between oil price shocks and US recessions is well-known. But, I find especially large supply elasticity estimates for construction machinery, where this story would not apply. Second, the sample periods from which I produce supply elasticity estimates are limited to the commodity boom periods, which fall primarily before the financial crisis and recession could have begun driving down other prices.

Another concern is the quality of the price indices I will use to measure machinery prices. The Producer Price Index data underlying the indices are based on monthly surveys of domestic manufacturers of machinery and attempt to measure all "changes in net revenues received by producers," including manufacturer-to-customer incentives like rebate programs and low-interest financing arrangements (Bureau of Labor Statistics [2008]). It is still feasible that, despite the best efforts of the Bureau of Labor Statistics, the indices fail to capture all relevant movements in machinery prices. If the indices systematically overestimate prices when they are low and underestimate prices when they are high, then price increases during commodity price booms could be underestimated, and supply elasticity estimates could be upward biased. However, the results from Goolsbee [1998] suggest that this effect could not be too large. His estimates suggest that a 10% investment tax credit would increase capital goods prices by 4% on average, and close to 10% for several types of equipment, including farm and mining machinery. If Goolsbee's estimates are correct, there cannot be much room for the PPI data to systematically understate price changes.

I thus find no concrete reasons to suspect that supply elasticity estimates will be biased upward. Nonetheless, the validity of results still rests on the assumption that there were no positive supply shocks keeping machinery prices low during the output price booms. If, for example, there was a series of exogenous, increasing, positive productivity shocks in machinery manufacturing during this period, then supply elasticity estimates could be biased upward. Aggregate productivity growth was low during the commodity boom years (Jorgenson, Ho, and Stiroh [2008], p. 6), so there is little reason to suspect there was a sustained productivity boom in machinery manufacturing during this time.

3 Data

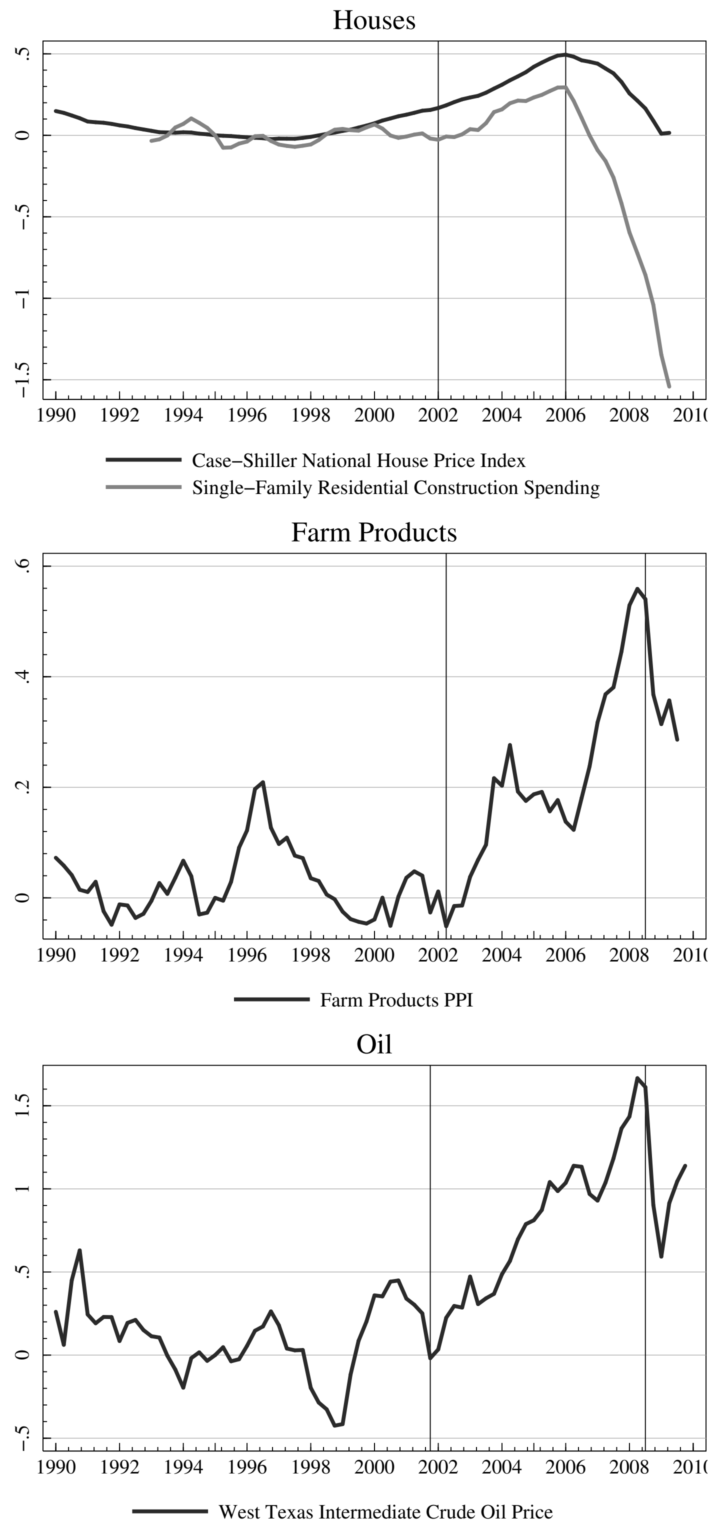
I use data from the National Income and Product Accounts of the Bureau of Economic Analysis (BEA) to measure both machinery prices and quantities. Quantity data are based on monthly surveys of shipments by U.S. manufacturers conducted by the Census Bureau. The BEA then adjusts these domestic production numbers for imports and exports using data from the International Trade Commission. The Bureau of Labor Statistics has its own monthly survey asking U.S. machinery manufacturers about the prices they receive for their output, and these data are used to create the Producer Price Indices (PPIs). The BEA uses the PPIs to create price indices and measure real investment quantities. I use the BEA real investment and price index series for construction machinery, farm machinery, and mining and oilfield machinery. This is the same source of the data used for many of the results in Goolsbee [1998]. To measure output price booms, I use the Case-Shiller National House Price Index, the Census Bureau's measure of construction spending on single-family homes, the PPI for farm products, and the spot price of West Texas Intermediate Crude oil.

I take logarithms of all series, regress them on a linear trend over the 15 years from 1988 to 2002, take the residuals, and subtract off the value from 1995q1. The resulting detrended output price series, normalized to 1995q1, appear in Figure 3. The recent boom and bust in prices is quite apparent in all three figures. Housing prices rose by more than 30% from 2002 to 2006, relative to their pre-2002 trend. Farm products prices rose more than 60%, and oil prices rose 150%.[5] Figure 3 also includes vertical lines that represent my subjective judgement of the beginning and end of commodity price booms based on the data in the figure. These are essentially the periods from trough to peak in the price series. However, the Case-Shiller price index is very smooth, so I use the trough of the singe-family residential construction spending series to date the beginning of the housing boom.

Figure 4 presents the detrended and normalized price and quantity series for all three machinery types. It is immediately clear from the figure that there have been large swings in quantities accompanied by small movements in prices for all three machinery types. For example, construction machinery quantities grew by 44% during the housing boom, while prices increased about 5%. Farm machinery quantities increased by 40%, with an 8% increase in prices. Mining machinery quantities increased by 75%, with about a 15% increase in prices. The data in Figure 4 provide very transparent evidence that quantities move far more than prices. Unless these movements were accompanied by large, well-timed supply shocks, the data graphed in Figure 4 already suggest that supply elasticities must be large.

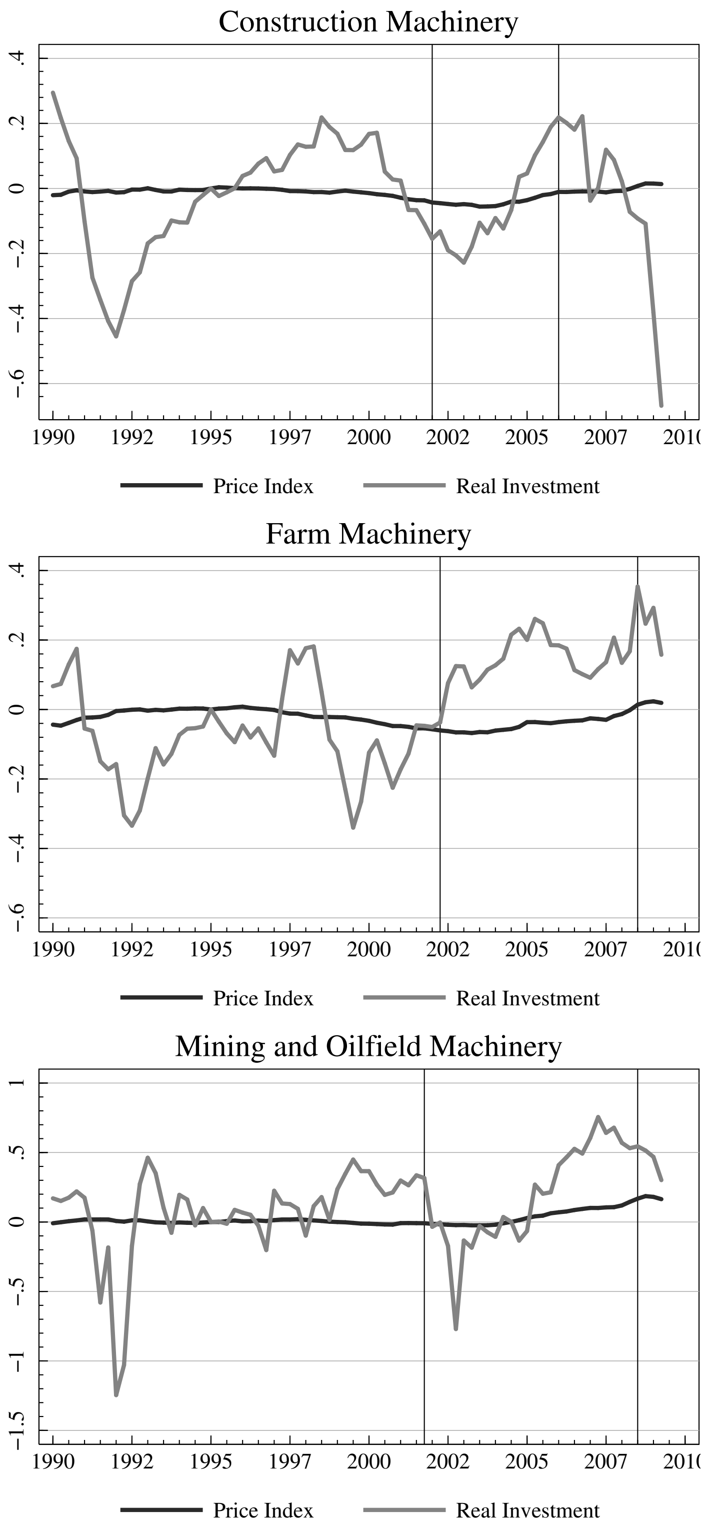
[5] These figures are actually changes in log points, which, of course, become poorer approximations to percentage changes when changes are large.

Figure 3: Recent Output Price Booms



All series logged, detrended, and normalized to 1995Q1. Vertical lines indicate the beginning and end of periods that I define as output price booms.

Figure 4: Machinery Prices and Quantities



All series logged, detrended, and normalized to 1995Q1. Vertical lines indicate the beginning and end of demand booms defined on the basis of output prices in Figure 3.

4 Results

Table 1 presents regression results for all three machinery types. Panel A presents results for construction machinery, Panel B for farm machinery, and Panel C for mining and oilfield machinery. Columns 1 and 2 present forward and reverse OLS regressions over the sample period from 1990 to the end of the relevant output price boom. I argued above that the forward and reverse estimates should provide lower and upper bounds on the supply elasticity when supply curves slope up and supply and demand shocks are uncorrelated. In panels A and C, the estimates in columns 1 and 2 provide only very wide bounds on the supply elasticity, suggesting that supply shocks may often be relevant in determining variation in prices and quantities. For construction machinery in Panel A, the forward elasticity estimate is 1.96, and the reverse estimate is 47.6. For mining machinery in Panel C, the forward estimate is 4.1 and the reverse is 15.9. In panel B, estimates suggest that farm machinery supply might be downward sloping.

Columns 3 and 4 again present forward and reverse OLS estimates, but limit the sample to the output price boom periods identified from Figure 3. Bounds on the elasticity estimate are much tighter. For construction machinery in Panel A, the forward elasticity estimate is 9.5, and the reverse estimate is 11.6. For farm machinery in Panel B, the forward estimate is 1.9 and the reverse is 6.8. For mining machinery in Panel C, the forward estimate is 5.1 and the reverse is 7.0.

Figure 5 presents a graphical depiction of results from Columns 3 and 4. Dots in the scatter plot are data points during the output price boom periods. The grey lines are forward regression lines, and the black lines are reverse regression lines. As in Figure 4 and Table 1, it is quite clear that supply curves are fairly flat.

Standard errors in Columns 1 through 4 are computed using the Newey-West estimator with a lag length of 4.[6] That is, they are robust to heteroskedasticity and correlation between

[6]The standard errors for the "reverse" elasticity estimates in Columns 2 and 4 are computed using the delta method around the reverse regression coefficient.

Table 1: Supply Elasticity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Construction Machinery							
Price Elasticity	1.960	47.618	9.460	11.587	13.002	13.399	23.572
	(1.449)	(52.289)	(1.082)***	(1.713)***	(1.959)***	(1.928)***	(19.237)
Manufacturing Compensation						2.165	1.442
						(1.207)*	(2.231)
Gross Domestic Product							-15.281
							(25.938)
Observations	65	65	17	17	17	17	17
R^2	.041	.041	.816	.816			
Firt Stage Coefficient					.205	.194	.153
Partial F Statistic					15.035	16.678	.829
Partial R^2					.501	.544	.060
Panel B: Farm Machinery							
Price Elasticity	-2.104	-22.426	1.877	6.788	1.897	2.552	2.583
	(1.176)*	(13.468)*	(.593)***	(2.752)**	(.712)***	(.988)***	(.977)***
Manufacturing Compensation						1.294	1.368
						(1.001)	(1.035)
Gross Domestic Product							.244
							(1.316)
Observations	75	75	26	26	26	26	26
R^2	.094	.094	.276	.276			
First Stage Coefficient					.107	.083	.085
Partial F Statistic					55.830	41.267	41.702
Partial R^2					.699	.642	.655
Panel C: Mining and Oilfield Machinery							
Price Elasticity	4.146	15.892	5.105	6.999	4.722	4.468	4.241
	(.824)***	(8.510)*	(.786)***	(1.129)***	(.637)***	(.853)***	(.738)***
Manufacturing Compensation						-1.480	.309
						(2.603)	(2.295)
Gross Domestic Product							11.219
							(3.468)***
Observations	75	75	28	28	28	28	28
R^2	.261	.261	.729	.729			
First Stage Coefficient					.121	.105	.105
Partial F Statistic					165.674	127.224	120.850
Partial R^2					.864	.836	.834

Columns 1 through 4 present OLS estimates of the price elasticity of machinery supply. Columns 1 and 3 are from the forward regression of log quantities on log prices. Columns 2 and 4 are from the reverse regression of log prices on log quantities. OLS standard errors are Newey-West with a lag length of 4. The standard error for the reverse regression is computed using the delta method around the point estimate. Columns 5 through 7 present just-identified IV estimates using the output price series from Figure 3 as instruments. Columns 1 and 2 use the sample from 1990 to the end of the relevant output price boom. Columns 3 through 7 limit the sample to the periods of output price booms identified from the data in Figure 3.

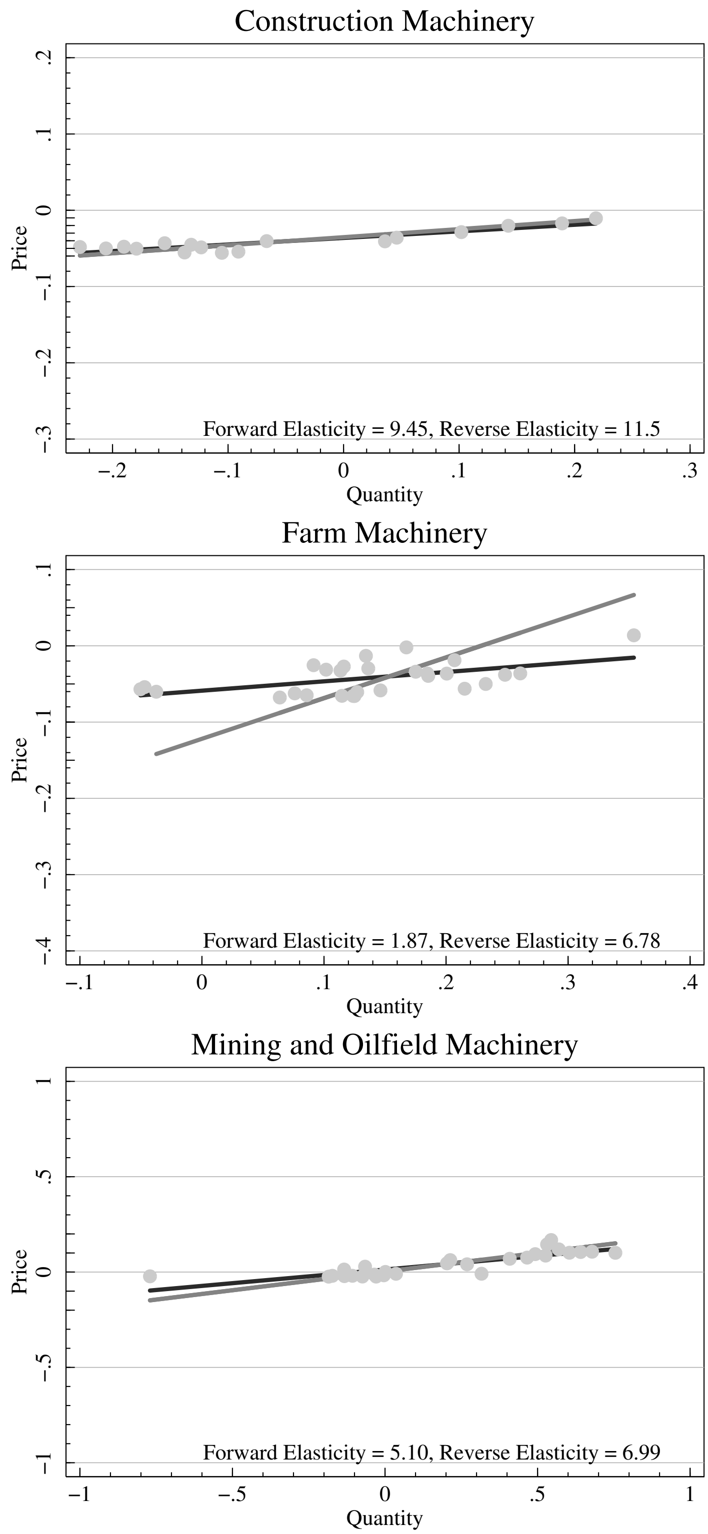
residuals up to four quarters away. In fact, the Newey-West adjustment has a very minor impact on the interpretation of results. Standard errors rise less than 30% with the Newey-West adjustment in all specifications. Because t-statistics are large, results remain highly significant.

Columns 5 presents instrumental variables estimates using the appropriate series from Figure 3 as an instrument for machinery prices. I use the series of single-family residential construction spending as the instrument for construction machinery prices because the Case-Shiller house price index is extremely smooth. Results differ relatively little from the OLS estimates in Columns 3 and 4. For construction machinery, the Column 5 estimate of 13.0 is a bit above the Column 4 estimate. For farm machinery, the Column 5 estimate of 1.9 is just above the Column 3 estimate. For mining machinery, the column 5 estimate of 4.7 is just below the Column 3 estimate.

Columns 6 and 7 present instrumental variables results where manufacturing compensation and gross domestic product are included as additional exogenous controls. The story that output price booms might push up aggregate demand and increase the cost of machinery manufacturing would suggest that including these controls might increase the estimated supply elasticities. Estimates do increase somewhat in Panels A and B, but, overall, results are quite similar when these controls are included.

All three panels include information useful in assessing the quality of the first-stage relationship between output prices and machinery prices. The posited relationship would suggest the coefficient on output prices should be positive, and all are. Partial F-statistics and R^2s are comfortably large in all panels and columns, with the exception of Panel A, Column 7. The estimated elasticity "blows up" in this specification, but the standard error is sufficiently large that results from other columns cannot be rejected. Considering all estimates from Table 1, I conclude that the supply elasticity of construction machinery is at least 10, that of farm machinery is around 2, and that of mining and oilfield machinery is around 5.

Figure 5: Machinery Prices and Quantities During Recent Output Price Booms



All series logged, detrended, and normalized to 1995Q1. Black lines are OLS regression lines from reverse (price on quantity) regressions. Grey lines are from forward (quantity on price) regressions.

Table 2: Pooled Sample Supply Elasticity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price Elasticity	.166	527.526	5.091	8.302	5.262	5.535	4.997
	(.677)	(914.090)	(.494)***	(.341)***	(.550)***	(.626)***	(.561)***
Manufacturing Compensation						1.134	2.253
						(.820)	(.738)***
Gross Domestic Product							6.340
							(1.322)***
Observations	195	195	71	71	71	71	71
R^2	.012	.13	.728	.814			
Firt Stage Coefficient					.111	.102	.100
Partial F-Statistic					213.496	210.252	196.273
Partial R^2					.761	.761	.751

Columns 1 through 4 present OLS estimates of the price elasticity of machinery supply. Columns 1 and 3 are from the forward regression of log quantities on log prices. Columns 2 and 4 are from the reverse regression of log prices on log quantities. OLS standard errors are Newey-West with a lag length of 4. The standard error for the reverse regression is computed using the delta method around the point estimate. Columns 5 through 7 present just-identified IV estimates using the output price series from Figure 3 as instruments. Columns 1 and 2 use the sample from 1990 to end end of the relevant output price boom. Columns 3 through 7 limit the sample to the periods of output price booms identified from the data in Figure 3.

Table 2 presents results where all three types of machinery are pooled together. In the year 2000, construction machinery accounted for 57% of total investment in all three machinery types, farm machinery for 31%, and mining and oilfield machinery for 12%. A simple weighted average of the coefficients from Table 1 would thus suggest a pooled supply elasticity around 7. I construct weights to account for the relative importance of these machinery types and the number of output boom quarters for each type, and these weights are used in the estimates in Table 2. As there is more variation in the output prices used to instrument for farm and mining machinery, these weighted estimates will place more importance on these equipment types than does the simple weighted average.

The forward and reverse OLS estimates in Columns 1 and 2 use the data beginning in 1990 and estimate very wide bounds on the supply elasticity. The estimates in Columns 3 and 4 use only the data from the output price boom periods, and estimate pooled supply elasticities of 5.1 and 8.3. The instrumental variables specifications in Columns 5, 6, and 7 produce estimates of 5.3, 5.5, and 5.0. I thus conclude that the aggregate price elasticity of supply for these three kinds of machinery is about 5.

5 Conclusions

Goolsbee [1998] estimated a capital supply elasticity around 1, while I have estimated an elasticity around 5. The discrepancy does not stem from the particular types of machinery that I have studied in this paper. Goolsbee [1998] presents estimates of the pass-through of investment tax credits into prices broken out by equipment types (p. 132). His estimate for construction machinery is more than 20% higher than his estimate for the pooled sample, and his estimates for farm and mining machinery are higher still. Thus we should expect lower supply elasticity estimates for these types of equipment than for Goolsbee's pooled sample.

A more likely explanation is that the market for machinery has changed since the 1962-1988 period covered by Goolsbee's data. Increased competition from imports has likely flattened supply curves for many kinds of capital goods. In Edgerton [2009], for example, I found that imports and exports of used machinery have become an increasingly important factor in the total supply of construction machinery to the United States. Results thus suggest that there is relatively little reason to be concerned that public policies intended to stimulate investment demand will simply push up the prices of investment goods.

Perhaps the most important change in the markets for investment goods over the last several decades has been the increasing dominance of computers, software, and communications equipment as a share of total investment. More research focused on the effects of public policies on these types of investment would be welcome.

6 Appendix: Derivation of Results in Section 2

Solve for p,

$$\begin{aligned} q &= \beta p + \epsilon_s \\ \gamma_1 p + \gamma_2 z + \epsilon_d &= \beta p + \epsilon_s \\ (\gamma_1 - \beta)p + \gamma_2 z + \epsilon_d &= \epsilon_s \\ (\gamma_1 - \beta)p &= \epsilon_s - (\gamma_2 z + \epsilon_d) \\ p &= \frac{\epsilon_s - (\gamma_2 z + \epsilon_d)}{(\gamma_1 - \beta)}. \end{aligned}$$

Plug into the OLS bias term,

$$\begin{aligned} \frac{cov(\epsilon_s, p)}{var(p)} &= \frac{cov(\epsilon_s, \frac{\epsilon_s - (\gamma_2 z + \epsilon_d)}{(\gamma_1 - \beta)})}{var(p)} \\ &= \frac{cov(\epsilon_s, \epsilon_s - (\gamma_2 z + \epsilon_d))}{(\gamma_1 - \beta) var(p)} \\ &= \frac{var(\epsilon_s) - cov(\epsilon_s, (\gamma_2 z + \epsilon_d))}{(\gamma_1 - \beta) var(p)}. \end{aligned}$$

Solve for q,

$$\begin{aligned} p &= \frac{\epsilon_s - (\gamma_2 z + \epsilon_d)}{(\gamma_1 - \beta)} \\ \frac{1}{\beta} q - \frac{\epsilon_s}{\beta} &= \frac{\epsilon_s - (\gamma_2 z + \epsilon_d)}{(\gamma_1 - \beta)} \\ q - \epsilon_s &= \frac{\epsilon_s - (\gamma_2 z + \epsilon_d)}{(\gamma_1 / \beta -)} = \frac{\beta \epsilon_s - \beta(\gamma_2 z + \epsilon_d)}{(\gamma_1 - \beta)} \\ q &= \frac{\beta \epsilon_s - \beta(\gamma_2 z + \epsilon_d)}{(\gamma_1 - \beta)} + \epsilon_s \frac{(\gamma_1 - \beta)}{(\gamma_1 - \beta)} = \frac{\gamma_1 \epsilon_s - \beta(\gamma_2 z + \epsilon_d)}{(\gamma_1 - \beta)}. \end{aligned}$$

Plug into the reverse OLS bias term,

$$
\begin{aligned}
\frac{cov(\epsilon_s, q)}{\beta var(q)} &= \frac{cov(\epsilon_s, \frac{\gamma_1\epsilon_s - \beta(\gamma_2 z + \epsilon_d)}{(\gamma_1 - \beta)})}{\beta var(q)} \\
&= \frac{cov(\epsilon_s, \gamma_1\epsilon_s - \beta(\gamma_2 z + \epsilon_d))}{(\gamma_1 - \beta)\beta var(q)} \\
&= \frac{\gamma_1 var(\epsilon_s) - cov(\epsilon_s, \beta(\gamma_2 z + \epsilon_d))}{(\gamma_1 - \beta)\beta var(q)} \\
&= \frac{\frac{\gamma_1}{\beta} var(\epsilon_s) - cov(\epsilon_s, (\gamma_2 z + \epsilon_d))}{(\gamma_1 - \beta) var(q)}.
\end{aligned}
$$

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