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Modeling Processor Market Power and the Incidence of Agricultural Policy
A Nonparametric Approach

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Johnson (1979) identified six justifications for government policy, including agricultural policy. One of these was the provision of a stable minimum level of income commensurate with that of other groups in society. Equally classic analyses of the incidence of agricultural subsidies have focused on comparing the deadweight loss across policies, given the amount of income transferred to farmers (Wallace 1962; Gardner 1983). For the most part, these policy analyses have assumed that agricultural markets are competitive enough that any market power on the part of processors can be safely assumed away and the market treated as perfectly competitive (Rude and Meilke 2004). Given this assumption, the focus of these analyses is efficiency, and the assessment of the economic cost of a particular support policy depends only on its deadweight loss and the size of the transfer to farmers. Russo, Goodhue, and Sexton (forthcoming), however, demonstrate theoretically that even small degrees of market power can enable processors to extract considerable rents from taxpayers, affecting the distribution of the benefits (and the costs) of the policy. Our analysis focuses on distribution, rather

than efficiency. Any distribution of policy rents to nonfarmer agents may make support policies less attractive politically.

The reliance on the perfectly competitive framework for analyzing policy incidence is interesting from a historical perspective. Reducing the exercise of market power in order to increase economic efficiency was among Johnson's other justifications for agricultural support policies. The economic history of agriculture suggests that it would be appropriate to address processor market power when analyzing government support policies. Farmer protests against the exercise of market power by other parties predate the major agricultural support programs developed in the 1930s; for example, the Grange and Populist movements in the nineteenth century were driven in part by farmers' protests regarding their perceptions of the exercise of market power against them in transportation and procurement (Stewart 2008). This earlier movement resulted in the Interstate Commerce Act of 1887. The Capper-Volstead Act of 1922, which exempted farmer cooperatives from antitrust regulations, was designed to enable farmers to organize collectively in order to exercise countervailing market power against buyers. In this chapter, we do not assess whether the current U.S. policy is effective in alleviating the consequences of market power on farmers. Instead, we focus on the unintended implications for welfare distribution of the interaction between middlemen's market power and government intervention.

This analysis examines the interactions between market power and agricultural policy in the U.S. wheat flour milling industry. It has two main objectives: to assess if the payments trigger a change in the underlying economic behavior of the milling industry, and to estimate if the spread between the price of wheat and the price of wheat flour is affected by the policy regime, holding everything else constant. Results indicate that wheat millers alter their pricing behavior when the program is making payments, and they are able to extract a rent from government intervention. These findings are consistent with a static model of oligopsony power. Theory suggests that deficiency payments reduce the elasticity of farmers' supply (e.g., Wallace 1962; Alston and James 2001). Consequently, the expectation is that, holding everything else constant, the oligopsony markdown is larger when the policy results in payments to farmers than otherwise. In this context, deficiency payments can be used as a natural experiment for identifying millers' oligopsony power, similar to other policy measures (Ashenfelter and Sullivan 1987).

Previous literature has tested for market power in the U.S. wheat flour milling industry. Brester and Goodwin (1993) found that the degree of cointegration of the price time series over space and across the vertical wheat chain was negatively correlated with the concentration of the largest four firms (CR4) index and argued that the increase in concentration was lessening competition. On the other hand, the price series exhibited a high degree of cointegration, consistent with the possibility that the industry remained competitive. Because the use of cointegration analysis may lead

to ambiguous conclusions, as it did in this instance, later studies have relied on structural models. Kim et al. (2001) used a Poisson regression model to investigate changes in industry structure and found evidence of oligopoly with price leadership. Stiegert (2002) tested for upstream and downstream market power in the U.S. hard wheat milling industry and found that the null hypothesis of perfect competition could not be rejected. These analyses did not take into account the possibility of interactions between government support policies and the exercise of market power in the wheat market. Russo, Goodhue, and Sexton (2009) did so using a standard New Empirical Industrial Organization (NEIO) approach (Applebaum 1982; Bresnahan 1989). This approach relies on shifts in supply, demand, or policy to identify the exercise of market power and identify its magnitude.

The test for market power in these structural models is, implicitly, a joint test regarding market power and the functional forms specified in the empirical model (Genesove and Mullin 1998). Consequently, the estimation is vulnerable to misspecification of cost, supply, and demand relationships (Perloff, Karp, and Golan 2007). Furthermore, the standard NEIO analysis leaves many questions regarding industry behavior and its impacts unanswered. When economic agents are strategic players, are market power parameters sufficient for describing their behavior? Theory suggests that this is not necessarily the case. Although the so-called agnostic interpretation of the NEIO market power coefficient is an effort to avoid this criticism, misspecification of the economic game can still lead to biased estimation (Corts 1999). Strategies may be more complex than simple Cournot strategies or may vary over time, such as collusion-sustaining price wars in oligopolies or oligopsonies (Green and Porter 1984).

In the case of government intervention in agriculture, the unbiasedness of the NEIO estimator is conditional on specifying the agents' strategic reaction to the policy correctly. Because this modeling choice requires prior information regarding agents' economic behavior that is not available in the case at hand, nonparametric techniques are used to characterize the pricing behavior of the wheat milling industry without introducing assumptions about the nature of the economic game governing processors' conduct and without specifying functional forms. A change in strategic behavior may be postulated if processors react to exogenous shocks in different ways when a policy is in effect than when it is not. Moreover, if the price margin under the policy regime is larger, then one may conclude that the millers are acting strategically to extract a rent from the policy at taxpayers' expense, ceteris paribus.

2.1   Background: The U.S. Wheat Milling Industry

U.S. farmers harvested 2.1 billion bushels of wheat from fifty-one million acres in 2007. The total value of production including government payments was $13.7 billion (National Agricultural Statistics Service 2008). Wheat pro-

duction is concentrated geographically; the three major production regions are the southern Great Plains (primarily Kansas and Oklahoma), the northern Great Plains (Montana and the Dakotas), and the Northwest (primarily southeastern Washington). The 2007 Census of Agriculture reported 160,818 farms classified as primarily wheat-producing farms (U.S. Department of Agriculture [USDA] 2007). The total number of farms producing wheat is even larger. Flour milling is the primary domestic use of wheat, although some is used for livestock feed and other purposes. The milling process generates both flour and by-products. By-products account for approximately 10 percent of the revenue from flour milling (Brester and Goodwin 1993).

The milling industry displays a number of characteristics that are consistent with an ability to exercise market power at the national level.[1] The four-firm concentration ratio in the flour milling industry is reasonably high and has increased over time. In 1974, the top four firms accounted for 34 percent of total milling capacity (Wilson 1995). In 1980, their share had increased slightly to 37 percent, further increasing to over 65 percent in 1991 (Brester and Goodwin 1993). Over that time period, consolidation was not limited to the firm level; between 1974 and 1990, the number of mills declined by a quarter, and the average plant capacity almost doubled (Wilson 1995). More recent data regarding concentration, the number of mills, or plant capacity are not available for the wheat flour industry alone; in 2007, the four-firm concentration ratio for the entire flour milling and malt manufacturing sector was 56.6 percent, and wheat flour milling accounted for 60 percent of the sector (IBISWorld 2007). Three of these large firms are large multicommodity agrofood firms; Archer Daniels Midland, ConAgra, and Cargill compete with each other across a number of markets, which potentially could strengthen their ability to collude. These firms increased their share of the number of wheat flour milling plants operated from 14 percent in 1974 to almost two-thirds in 1992 (Wilson 1995).

Between the mid-1970s and 1997, per capita wheat consumption increased, even though its share of total per capita grain consumption declined. There are a number of factors that may have contributed to this increase, including increased consumption of meals away from home, increased awareness of the health benefits of eating grain-based foods, and the promotion of wheat products by industry organizations (Vocke, Allen, and Ali 2005; Brester 1999). Since 1997, per capita wheat consumption has declined, due in part to a new technology for extended shelf life bread that has reduced the share of unsold bread and due in part to an increased interest in low-carbohydrate diets (Vocke, Allen, and Ali 2005). Another factor behind the continuing decline in wheat's share of total grain consumption has been increased con-

1. In theory, it is possible that any market power exercised by millers is due to local monopsony power.

sumer interest in eating a variety of grain products, driven in part by an increasingly diverse population (Putnam and Allshouse 1999).

Wheat is one of the major agricultural support program commodities, and government payments are a nonnegligible share of farm income for wheat producers. For farms characterized as primarily wheat producers, government payments were approximately 20 percent of average gross cash income in 2003. Government payments to other wheat-producing farms were about 8 percent of average gross cash income (Vocke, Allen, and Ali 2005). These numbers are quite dependent on the difference between the policy price set by the government and the market price; in 2007, average government payments equaled 5 percent of the market value of agricultural products sold for farms characterized as primarily wheat producers (USDA 2007).

U.S. farm policy is governed primarily by federal "farm bills" legislated every few years. Wheat producers were eligible for three basic types of program payments during the period of study (1974 to 2005), although implementation details differed. Direct payments are not linked to market conditions, while countercyclical payments depend on a season's average market price. Beginning with the 1985 Farm Bill, direct and countercyclical payments were restricted to a share of production defined by base acres and base yields. Federal commodity loan and marketing loan programs are the source of the third type of payment. Historically, these programs were intended to promote orderly marketing by providing farmers with income at harvest time that enabled them to repay operating loans without forcing them to sell their crops. Because farmers could wait to market their production, harvest-time prices would not be depressed by credit-driven sales. In addition to promoting orderly marketing, loan programs have become an important source of farm income support in years with low market prices.

Some variant of a commodity loan program has been available to farmers since the 1930s. Under a loan program, a farmer pledges a specified quantity of wheat as collateral for a loan valued at that quantity of wheat multiplied by the loan price. Farmers can choose to repay loans at the market price, rather than the loan price, when the market price is lower. Depending on the year, repayment could occur via forfeiting the actual physical product (a nonrecourse loan) or redeeming commodity certificates as well as through an exchange of funds. The resulting difference in price is referred to as a "marketing loan gain." Alternatively, for some years in the sample, the farmer could choose to receive a loan deficiency payment in lieu of an actual loan. The policy price on which loan deficiency payments and marketing loan gain payments are calculated is the loan rate. The relevant market price for loan repayments is the "posted county price" set daily by the government. It is intended to reflect market conditions in a county by adjusting major market prices for transportation costs and temporary cost differences. Farmers can lock in the loan rate as the price for their production by choosing to

repay their loan at the posted county price rather than the loan rate, resulting in a marketing loan gain, or by requesting a loan deficiency payment in the amount of the difference between the two prices on a given day.

We focus on loan deficiency payments and marketing loan gains for three reasons. First, some variant of this program has been available to producers throughout the study period. Second, there has been no change in the share of production eligible for at least one of these payments. Finally, whether farmers receive payments is linked to the market price via the posted county price.

2.2   Oligopsony Power and Marketing Loan Rates

This analysis addresses the possibility that a marketing loan policy may enable millers with oligopsony power to increase their margins. Figures 2.1 to 2.3 illustrate the argument graphically by comparing the effects of a marketing loan policy under perfect competition and monopsony. Units are normalized so that one unit of wheat produces one unit of flour and normalize millers' production costs other than wheat to zero. Cases where the loan rate is the relevant price for farmers are referred to as cases where the marketing loan policy binds.

Under perfect competition, the market price P^* is determined by the intersection of supply and demand. If the loan rate is lower than the perfectly competitive expected price ($LR < P^*$), then farmers will repay the loan, and the loan price will not affect the market outcome. If the loan rate is higher than the perfectly competitive expected price ($LR > P^*$), as depicted in figure 2.1, then farmers will increase production because the loan rate is the effective price they receive. In this case, production $Q_s(LR)$ is independent of the market price. Millers will pay farmers the price $P_d[Q_s(LR)]$ defined by the demand curve.

Figures 2.2 and 2.3 address the effects of the marketing loan program when the miller is a monopsonist. If the loan rate is lower than the price the miller would pay farmers in the absence of the policy (P_o), then the market price determines output Q_o (figure 2.2). The margin received by the miller, defined as the difference between the price of flour and the procurement price of wheat at the quantity produced, equals $W_o - P_o$. If the loan rate is higher than P_o, then the policy is binding. Production is determined by the loan rate and is independent of the market price. The equilibrium quantity $Q_s(LR)$ is found by evaluating the supply function at the loan rate.

Given that supply is perfectly inelastic with respect to the market price when the policy binds, the price the miller pays farmers is indeterminate. Institutional factors suggest that millers are in a relatively strong position to extract policy rents by reducing the market price of wheat. Obviously, farmers have a weaker incentive to bargain for a higher price and greater
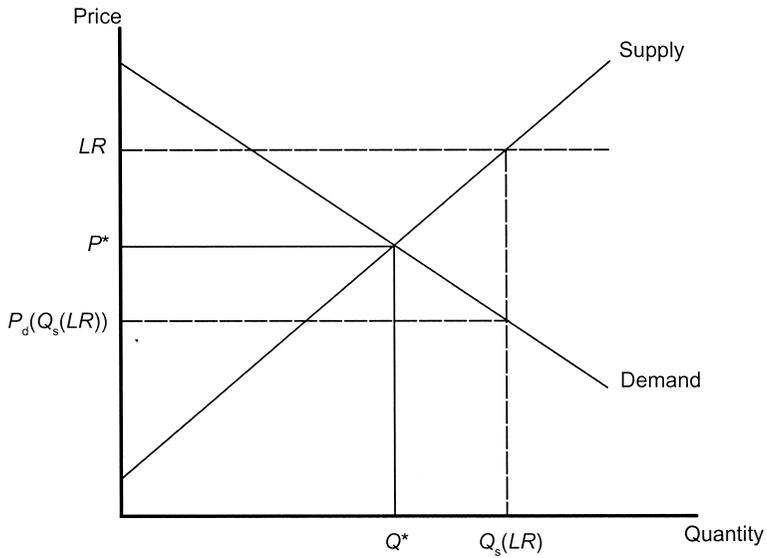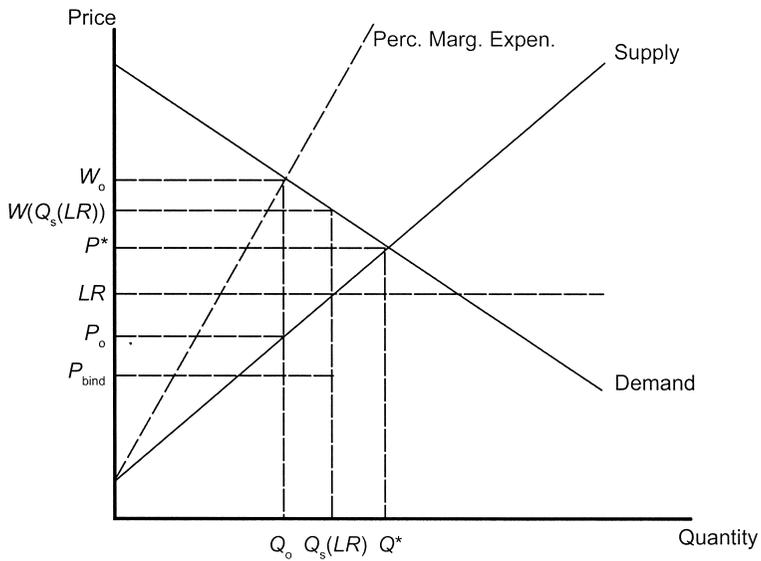
Fig. 2.1 Marketing loan program under perfect competition

Fig. 2.2 Marketing loan program under oligopsony: Loan price below perfectly competitive price and above market price
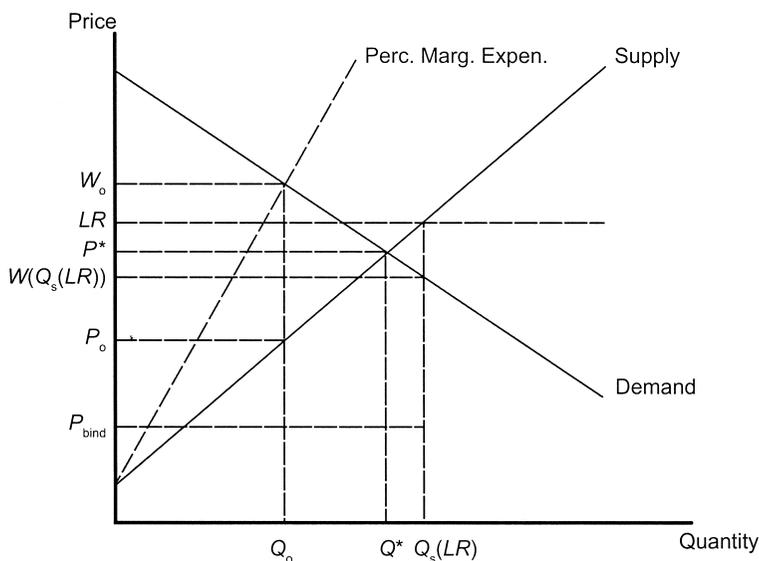
Fig. 2.3   Marketing loan program under oligopsony: Loan price above perfectly competitive price

share of the surplus under a marketing loan program than in an unregulated market. When offered a low price, they are less likely to continue to incur the cost of keeping their wheat in storage because any expected gain of selling the wheat later is (at least partially) offset by the loan rate-based government payment they receive.

Furthermore, as discussed earlier, the wheat milling industry is relatively concentrated, while there are a very large number of wheat-producing farms. Consequently, individual farmers have relatively little ability to negotiate effectively.[2] These factors are reflected in the organization of farmgate grain markets; generally prices are set by buyers and farmers choose whether to accept the take-it-or-leave-it offer.

There are two cases of binding policies defined by the relative magnitude of the loan rate and the perfectly competitive price. The first case of a binding policy is shown in figure 2.2. If the loan rate is higher than P_o and lower than P^*, then farmers produce more as a result of the policy. The miller maximizes profits by paying farmers a farmgate price no more than the loan

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2. While some wheat farmers sell their output through marketing cooperatives, and the share of wheat marketed via cooperatives was nonnegligible during the sample period, the number of cooperatives is too large to suggest that there may be off-setting oligopoly power. In 1973, a total of 1,965 cooperatives as a group accounted for 29 percent of first-handler sales. In 1993, 1,243 cooperatives accounted for 38 percent of first-handler sales (Warman 1994).

rate LR. As can be seen in the figure, at LR, the loan marketing program reduces the miller's margin, all else equal. At farmgate prices no higher than P_{bind}, the miller's margin would increase.

The second case of a binding policy is shown in figure 2.3. If the loan rate is higher than P^*, then the farmgate price will be no higher than the price that will equate the quantity demanded with the quantity produced in response to the loan rate, or $W[Q_s(LR)]$. At that upper bound, the miller will have a zero margin. At prices no higher than P_{bind}, the miller's margin would increase.

The maximum price that the miller would be willing to pay farmers results in a lower margin when the policy binds than when the policy does not bind in both cases. Intuitively, the result is driven by the assumption that, if the policy is binding, farmers' supply is less elastic and the markdown of the farmgate price due to oligopsony power is expected to increase. Consequently, whether the marketing loan program allows millers to increase their margins is an empirical question. This analysis considers whether millers are able to drive the price sufficiently low when the policy is binding that they increase their margins.

2.3   Methodology

The structure of the empirical test regarding the millers' margin is simple. Define Y as the millers' margin calculated as the difference between the price of a hundredweight of wheat products and the price of the equivalent quantity of wheat, d as a dummy variable defining the policy regime (d = 1 if the policy's target price is above the procurement market price, and d = 0 otherwise), and X as a matrix of exogenous variables representing supply, demand and millers' marginal cost shifters. The null hypothesis

$$H_0: E(Y|X,d = 0) = E(Y|X,d = 1)$$

is tested versus the alternative hypothesis

$$H_1: E(Y|X,d = 0) < E(Y|X,d =1),$$

where $E(Y|X,d) = f(X,d)$ and f is a function linking the exogenous variables and the policy regime to the conditional mean of Y. Rejection of the null hypothesis is statistical evidence that, holding everything else constant, the millers' margin increases if the policy is binding. Given our theoretical model, we interpret this result as a consequence of millers' oligopsony power.

Running the test is problematic because there is no clear and reliable a priori information about the linking function $f(X,d)$ and which variables are in the matrix X. Consequently, the test may be biased because of possible model misspecification or arbitrary exclusion restrictions. Much of the

literature on competitive behavior addresses this information problem by introducing assumptions regarding the linking function and using information available a priori regarding the "most important" exogenous variables, such as marginal-cost components, demand shifters, or supply shifters. It is widely acknowledged that these studies are joint tests on the assumptions regarding the behavioral model, the link functions, and the exclusion restrictions (Genesove and Mullin 1998; Corts 1999). An alternative approach to the information problem is based on pairwise comparisons of alternative models or nested models (e.g., Gasmi, Laffont, and Vuong 1992; Karp and Perloff 1993). This strategy shares two major limitations with the first approach: it relies on specific assumptions regarding demand and cost functions, and it selects the alternative that fits the data best among those tested, which does not necessarily correspond to the true data-generating process.

Given the challenges involved in implementing either of these approaches satisfactorily, this section presents a nonparametric approach that is able to compare the conditional expectations in the policy regimes even in the absence of information about the link function and without imposing arbitrary exclusion restrictions in the matrix of the exogenous variables. Assume that the available information can be divided into two matrices: a $T \times S$ matrix of all observable exogenous variables (X) that may or may not affect millers' pricing behavior and a $T \times 1$ vector representing the millers' margin (Y). The goal is to calculate the conditional mean of Y without knowing which variables in X are relevant and without knowing the function linking Y to X. The nonparametric approach used here addresses the two problems separately using a two-step procedure (Russo 2008).

The first step uses a sliced inverse regression (SIR) to identify the linear combination of the exogenous variables (the SIR factors) that are the best predictors for the millers' margin (Li 1991). The use of this dimension-reduction technique eliminates the need to use arbitrary exclusion restrictions and specify functional forms in the estimation of the conditional expectation. This step allows us to run the test even in the absence of reliable a priori information regarding the relevant explanatory variables. We collect the largest possible matrix X and use SIR to collapse it into a small (and manageable) set of factors.

The second step uses the SIR factors as the independent variables in nonparametric Nadaraya-Watson regressions (NW) in order to compare how the millers' margin changes with changes in the independent variables for years in which the policy resulted in payments to farmers to those for years when it did not (Nadaraya 1964; Watson 1964). The use of kernel estimators does not require imposing assumptions about the unknown linking function. Consequently, it is possible to estimate the conditional means and variances of the millers' margins under the two policy regimes. A simple test on the equality of means allows us to establish if the two estimates are significantly different.

The logic motivating this approach is intuitive. The obvious methodological approach to estimating how the exogenous variables affect the margin without imposing specific function forms is to use nonparametric regression techniques. Yet if S, the number of possible exogenous regressors, is large, this approach is likely to suffer from the *curse of dimensionality:* adding extra dimensions to the regression space leads to an exponential increase in volume, which slows the rate of convergence of the estimator exponentially. In order to avoid this curse, the original variables are compressed into a smaller number of factors that are linear combinations of the variables using SIR.

Importantly, the use of SIR factors in the second-stage regression does not prevent linking the pricing behavior of the milling industry to the original S exogenous variables. The SIR factors are linear combinations of the original variables. The coefficients are estimated by decomposing the consistent estimator of M, the variance-covariance matrix of $E(X|Y)$. Accordingly, the coefficients for the original variables can be computed and their significance tested (Chen and Li 1998).

One drawback to the standard SIR approach is that the factors it identifies are not necessarily interpreted easily using economic theory, which can make it challenging to utilize the results to identify plausible behavioral models. In order to address this shortcoming, the SIR was reestimated with a set of constraints restricting the number and composition of dimension-reduced shifters to correspond to the predictions of economic theory. The results are not affected substantially by the constraints. Thus, while testing for difference in the millers' margins, we obtain additional information about the underlying economic model governing the industry's behavior.

The restricted model uses Naik and Tsai's (2005) constrained inverse regression approach (CIR), a special version of SIR, which enables the classification of the exogenous variables in the matrix X as possible shifters of demand, farmer supply, or processor nonwheat marginal costs ex ante, using economic theory. Formally, given q linear constraints of the form $A'\beta = 0$ (where A is the $S \times q$ constraint matrix), the constrained efficient dimension reduction directions are given by the principal eigenvector of $(I - P)$ cov$[E(z|y)]$, where $P = \tilde{A}(\tilde{A}'\tilde{A})^{-1}\tilde{A}$ and $\tilde{A} = \Sigma_{xx}^{-1/2}A$. The output of the CIR is dimension-reduced shifters (DRS) that are linear combinations of exogenous variables, summarizing—in the case at hand—the effects of demand, supply, and marginal cost shifters, respectively.

The link function F_0 is estimated by regressing Y non-parametrically on the L linear combinations of X instead of on the S original variables. Using the consistent estimates of the βs (instead of the true values) in a kernel regression does not affect the first-order asymptotic properties of the estimator, and the error term has the same order of magnitude (Chen and Smith 2010). The output from this step allows the examination of how shifts in the significant SIR and CIR factors affect the millers' margin in binding and nonbinding policy years.

Table 2.1   **Descriptive statistics: Real prices for wheat and wheat products by location, 1974–2005**

	Wheat price		Wheat products price		Price margin	
	Minneapolis	Kansas City	Minneapolis	Kansas City	Minneapolis	Kansas City
Mean	9.30	8.87	11.44	10.98	2.14	2.10
Standard deviation	1.57	1.51	1.64	1.43	0.49	0.24
No. of observations	32	32	32	32	32	32

Source: USDA Wheat Yearbook 2006, available at http://www.ers.usda.gov/data/wheat/wheatyearbook .aspx.

2.4   Data

The data set contains information on wheat prices, flour prices, and other variables for 1974 to 2005. Data have been deflated using the producer price index (base year 1982) provided by the Bureau of Labor Statistics. The prices of wheat and wheat flour are those reported in the USDA's *Wheat Yearbook* for two locations: Kansas City and Minneapolis.[3] These cities are traditional areas of geographic concentration for wheat milling because they are major markets near important wheat production regions (Wilson 1995). The price of wheat is reported in terms of the cost to produce a hundredweight of flour, and flour and by-product prices are reported directly. The price margin is defined as the difference between the price of a hundredweight of flour and by-products and the price of the wheat used to produce it.

Table 2.1 reports descriptive statistics for these price series by market. Average real prices in Minneapolis are higher, although the difference is not statistically significant at the 90 percent confidence level. Real price margins are similar in the two markets: the average was equal to $2.14/hundredweight of flour in Minneapolis and $2.10/hundredweight in Kansas City. Figure 2.4 illustrates the real price trends in the two markets.

Table 2.2 reports descriptive statistics for the other variables in the data set. The data sources are the USDA, the Bureau of Labor Statistics, the Census Bureau, the Energy Information Agency, the University of Michigan, and the World Bank. Increases in the cost of fertilizer per acre (FERT), agricultural fuel per acre (FUEL) and hired agricultural labor per hour (HLB) are predicted to shift farmer supply upward. The policy price (POL) is predicted to increase supply when the policy is binding. Increases in hourly manufacturing wages (RHW), the price of gas (GAS), the transportation price index (TPI), and the bank prime loan rate (IR) are predicted to shift processors' nonwheat marginal cost up. Demand is predicted to shift out as population (USPOP), per capita income (USINC), wheat weight (WGHT) and protein content (PRTN)—as proxies for quality, the share of the population that

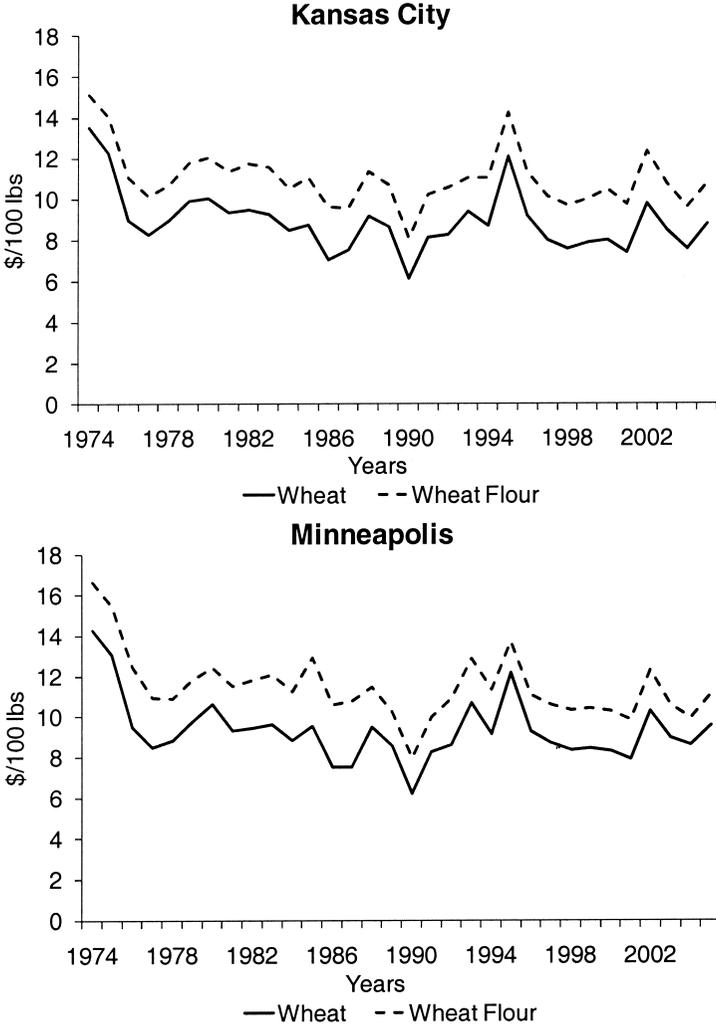3. Firm-level price data are not available publicly.

Fig. 2.4   Real prices of wheat and wheat products by location: 1974–2005

identifies as caucasian (CAUC), and per capita income in Japan (JINC), the largest importer of U.S. wheat during the sample period, increase.[4] Table 2.3 reports the pairwise correlation matrix of these variables. In addition, a

4. The analysis is limited to the market for wheat. Of course, in reality, farmers' wheat production is part of a larger acreage allocation decision. Depending on the region, barley, canola, corn, hay, rye, and other crops are substitutes in production for wheat. Including data regarding farmers' potential substitutes for wheat would introduce endogeneity concerns. Consequently, the analysis does not include data regarding the production, spot market prices, policy prices, or futures prices of substitute crops. Similarly, the Conservation Reserve Program (CRP) competes with wheat and other crops for acreage, although multiyear contracts limit its endogene-

Table 2.2   Descriptive statistics: Explanatory variables, 1974–2005

Variable	Definition	Mean	Min.	Max.	Standard deviation
FERT	Cost of fertilizer (real $/acre)	16.0	9.3	23.0	3.0
FUEL	Cost of agricultural fuel (real $/acre)	8.4	5.1	14.3	2.1
HLB	Cost of hired labor (real $/hour)	3.1	1.9	5.3	0.9
POL	Policy price (real $/hundredweight flour)	9.6	6.0	13.5	2.2
RHW	Industry wages (real $/hour)	15.3	14.7	16.3	0.5
GAS	Gas price (real $)	112.2	76.4	193.7	25.9
TPI	Transportation price index	114.3	45.8	173.9	35.5
IR	Bank prime loan rate (%)	9.0	4.1	18.9	3.2
USPOP	U.S. population (millions)	251.9	213.3	293.9	25.3
USINC	U.S. per capita income (real $)	4.1	1.1	9.5	2.6
WGHT	Wheat weight (pounds/bushel)	60.4	58.4	61.6	0.7
PRTN	Wheat protein content (%)	12.1	11.2	13.4	0.6
CAUC	Caucasian share of population (%)	0.8	0.8	0.9	0.0
JINC	Japan per capita income (real $)	90.6	56.7	103.8	13.3

Kansas City dummy variable (KANS) is included in order to allow for any location-dependent effects.[5]

The data set includes a dummy variable identifying the years when the policy is binding (BIN), that is, years in which the policy price is higher than the market price. Although the posted county prices are announced daily, data limitations require the use of less frequent observations.[6] Consequently,

ity to some extent. On the other hand, the criteria for acreage selection varied by enrollment round. Depending on the type of environmental protection targeted, the importance of CRP as a competitor for wheat varied considerably during the sample period. The analysis does not attempt to control for the farm crisis of the early 1980s because it was generated in part by low commodity prices.

5. The USDA time series for Kansas City prices is for No. 1 hard winter wheat, and the Minneapolis price series is for No. 1 dark northern spring wheat. Thus, the location dummy may include quality-related effects not captured by the weight and protein variables, as well as other factors that differ between the two locations.

6. Choosing the frequency of data was a difficult modeling decision. Annual data balance competing concerns regarding the unit of observation. Because wheat is storable, more frequent observations are more likely to be influenced by short-term storage decisions by farmers and millers. Farmers market their entire wheat crop within a year, except under very unusual conditions, and millers seldom hold flour more than one or two months (Brorsen et al. 1985). Inventories of wheat do extend across crop years; they are not addressed here due to the complications created by the presence of government-owned and exporter-owned stocks. On the other hand, as discussed in the preceding, the actual policy is implemented on a county-day basis. Incorporating this complexity into our analysis would be difficult, if not impossible, due not least to the increasing importance of storage as the frequency of observations increases. An additional practical difficulty is that some of the variables are provided on an annual basis, such as wheat quality. Specifying a time period that is less than a year would make it more difficult to collect information on exogenous variables, as would specifying a smaller unit of observation, such as a county or even a state. The National Agricultural Statistics Service reports that over 1,800 counties in forty-two states harvested wheat acreage in 2005 (National Agricultural Statistics Service 2010).

Table 2.3   **Correlation matrix**

	FERT	FUEL	HLB	POL	RHW	GAS	TPI	IR	USPOP	USINC	WGHT	PRTN	CAUC	JINC	Price margin
FERT	1.00														
FUEL	0.51	1.00													
HLB	-0.32	-0.08	1.00												
POL	-0.43	0.03	0.26	1.00											
RHW	0.34	0.18	-0.73	-0.53	1.00										
GAS	0.72	0.85	-0.32	-0.30	0.50	1.00									
TPI	0.68	0.48	0.02	-0.38	0.23	0.72	1.00								
IR	-0.21	0.24	-0.01	0.36	-0.26	-0.11	-0.45	1.00							
USPOP	0.68	0.36	-0.09	-0.54	0.39	0.69	0.97	-0.56	1.00						
USINC	-0.47	-0.12	-0.14	0.11	0.00	-0.35	-0.82	0.62	-0.79	1.00					
WGHT	-0.02	-0.07	-0.39	-0.33	0.31	-0.06	-0.34	0.15	-0.26	0.42	1.00				
PRTN	-0.01	0.16	0.25	-0.11	-0.03	0.14	0.26	0.04	0.23	-0.06	-0.37	1.00			
CAUC	-0.66	-0.32	0.09	0.49	-0.35	-0.62	-0.85	0.51	-0.88	0.67	0.21	-0.16	1.00		
JINC	0.41	0.32	0.33	-0.03	-0.16	0.42	0.87	-0.30	0.77	-0.87	-0.51	0.27	-0.63	1.00	
Price margin	-0.04	-0.03	-0.11	0.39	-0.13	-0.08	-0.17	0.03	-0.21	-0.09	-0.04	-0.26	0.26	-0.05	1.00

Note: See table 2.2 for explanation of abbreviations.

the years in which the policy was binding are defined using USDA yearly average data. A binding year (BIN = 1) is defined as one in which the average market price in that location is lower than the average "policy" price. The policy price is defined as the average yearly loan rate from 1996 on and is the maximum of the average yearly loan rate reported by the USDA and the target prices of deficiency payments prior to 1996 (before this date, all production was eligible for deficiency payments so the program provided the same incentives as the marketing loan program). Because both the policy and the market prices vary over the sample period, one does not expect, necessarily, that binding policy years correspond exactly to those years with lower market prices.

Figures 2.5 and 2.6 confirm that expectation. Figure 2.5 plots the policy price against the market price for the Kansas City market, distinguishing between binding and nonbinding years. Figure 2.6 plots the same information for the Minneapolis market. The figures are quite similar. While for the very highest market prices the policy is never binding, there is no clear pattern between the realized market price and whether the policy binds. The policy price appears to be the primary determinant. This pattern is consistent with the policymaking process. Prior to the 1985 Farm Bill, agricultural price support program parameters were set for the next few years in each farm bill and were not adjusted for market conditions (Love and Rausser 1997). Since 1985, national marketing loan rates have continued to be set as part of farm bills and do not respond to market conditions (USDA 2009).
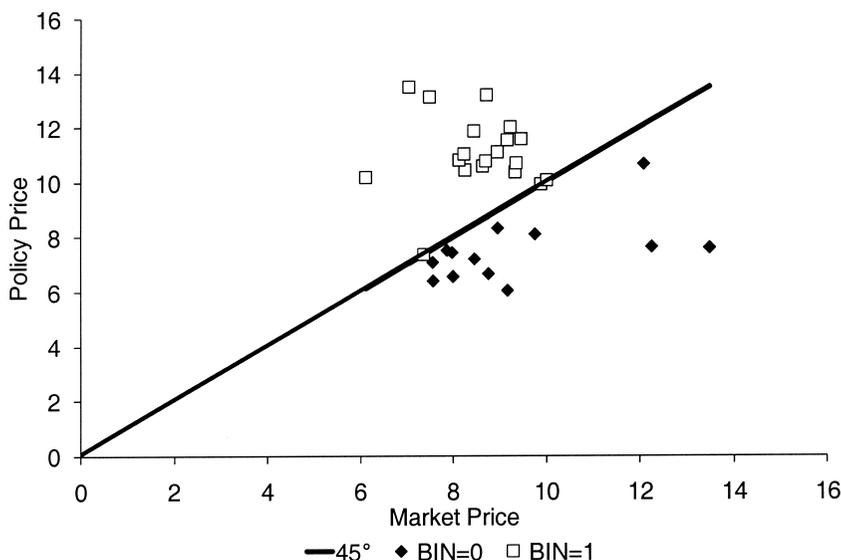

Fig. 2.5   Market and policy prices, binding and nonbinding policy years: 1974–2005, Kansas City
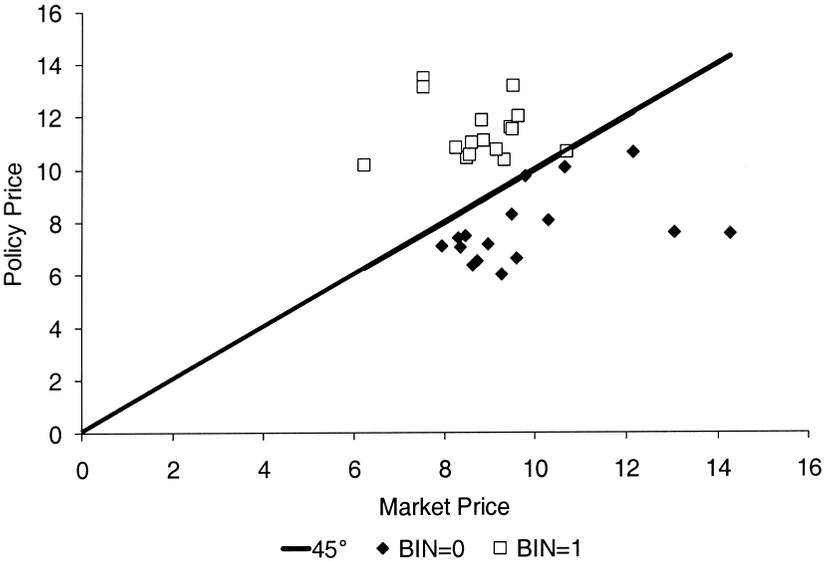
Fig. 2.6   Market and policy prices, binding and nonbinding policy years: 1974–2005, Minneapolis

2.5   Sliced Inverse Regression Results

Table 2.4 reports the results of the SIR estimation. SIR identifies two significant factors in the data. Factor one increases in a statistically significant fashion with the price of gasoline. It decreases when the following variables increase: wheat protein content, farmers' cost of hired labor, the price of fertilizer, the transportation price index, the policy price, the percentage of the population that identifies as caucasian, and the Kansas City dummy. The second factor increases significantly with wheat weight and the gasoline price and decreases with the price of fertilizer, the interest rate, the policy price, and the Kansas City dummy.

2.5.1   SIR Factors and the Policy Regime

Figures 2.7 and 2.8 plot realizations over time of the two SIR factors, distinguishing between years when the policy was binding and years when it was not. In figure 2.7, the first factor decreased steadily until the mid-1990s, then remained stable until about 2000, when it began declining again. There is no clear link between the level of the factor and whether the policy is binding. The second factor displays less of a trend over time, as shown in figure 2.8. It tended to have higher realizations in years when the policy was not binding. Figure 2.9 plots realizations of the second factor by realizations of the first factor, again distinguishing between binding and nonbinding policy years. As the figure demonstrates, there is no clear link between the relationship

Table 2.4   **Results: Sliced inverse regression**

| | Dimension-reduced factor | | | |
| | Factor 1 | | Factor 2 | |
	Coefficient	t-statistic	Coefficient	t-statistic
FERT	−4.65	−79.91**	−0.44	−6.55**
FUEL	0.47	2.66**	−0.22	−1.18
HLB	−3.73	−17.51**	0.10	0.42
POL	−10.58	−63.21**	−1.14	−6.37**
RHW	0.54	0.78	0.25	0.33
GAS	1.21	72.36**	0.87	48.69**
TPI	−5.84	−89.98**	−0.04	−0.60
IR	0.19	1.56	−0.96	−7.36**
USPOP	0.02	0.19	0.06	0.63
USINC	0.00	0.00	0.17	0.89
WGHT	−0.17	−0.79	0.86	3.79**
PRTN	−0.61	−3.24**	−0.27	−1.33
CAUC	−24.44	−2.39**	−2.94	−0.27
JINC	0.01	0.10	0.00	0.00
KANS	−0.37	−2.27**	−0.53	−3.09**

Notes: See table 2.2 for explanation of abbreviations. KANS = Kansas City dummy variable.
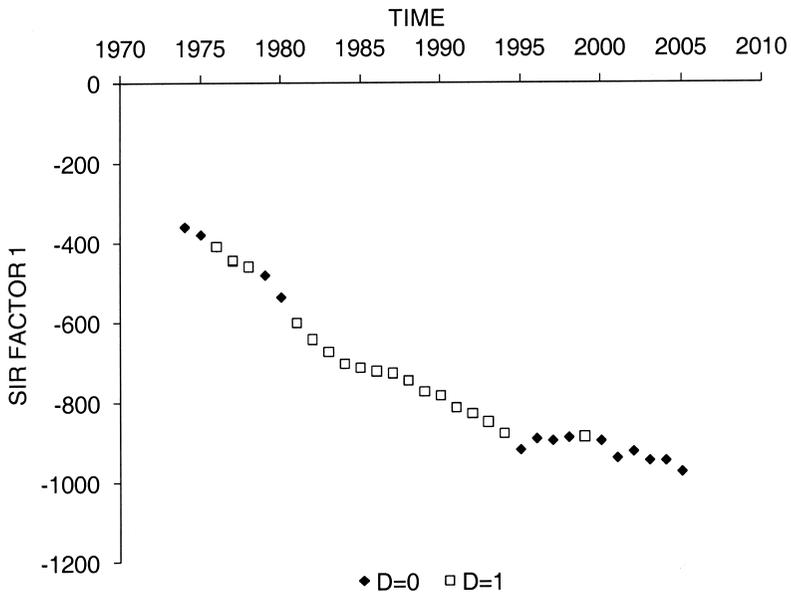
**Significant at 5 percent level.

Fig. 2.7   Realizations of the sliced inverse regression (SIR) first factor: 1974–2005, binding and nonbinding policy years

Fig. 2.8   Realizations of the sliced inverse regression (SIR) second factor: 1974–2005, binding and nonbinding policy years

Fig. 2.9   Realizations of the sliced inverse regression (SIR) first and second factors: binding and nonbinding policy years

of the two SIR factors and whether the policy is binding even though the coefficient on the policy price is statistically significant for both factors.

2.6   Constrained Sliced Inverse Regression Results

Table 2.5 reports the CIR results. It includes the constrained efficient dimension reduction directions and the *t*-statistics for each coefficient on the exogenous variables in each DRS.[7] Overall, the CIR performs well. The signs of the coefficients match predictions. In the demand DRS, the U.S. population, Japanese per capita income, the share of the U.S. population identifying as caucasian, and wheat weight have statistically significant coefficients with the predicted signs. The Kansas City dummy has a statistically significant positive coefficient. In the farmer supply DRS, all three input costs have statistically significant coefficients with the predicted sign. In the miller marginal cost DRS, wheat weight and wheat protein content have statistically significant coefficients. The costs of nonwheat inputs have statistically significant, negative coefficients, as predicted. The Kansas City dummy has a statistically significant negative coefficient.

2.6.1   DRS and the Policy Regime

The CIR results allow us to examine the relationships between the three DRS and the policy regime. Figures 2.10 to 2.12 illustrate the distribution of the DRS over time, differentiating between binding and nonbinding policy years. The figures show that there is a concentration of binding years before the 1996 policy reform, when the policy target price was relatively high. The binding policy years are not associated with particularly low or high realizations of the demand or marginal cost DRS. Realizations of the supply DRS tended to be lower in nonbinding policy years.

Figures 2.10 to 2.12 each plot the realizations of a single DRS for binding and nonbinding policy years. Thus, they do not address the possibility that binding policy years are characterized by interactions between the realizations of the DRSs that lead to low prices. Figures 2.13 and 2.14 examine this possibility. Figure 2.13 plots the policy regime against the demand and farm supply DRS. To fix ideas, years in which the demand DRS has a large realization and the supply DRS has a small realization appear in the bottom right-hand quadrant of the graph. In a partial equilibrium graph of a market, these points would correspond to market outcomes with relatively high prices and low quantities. For a given realization of the demand DRS,

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7. The signs of the coefficients in the farmer supply DRS are reversed relative to the conventional format of theoretical predictions in the table. That is, the positive signs on the cost of hired labor, fertilizer, and agricultural fuel indicate that an increase in any of these costs will shift supply inward. This is simply an artifact of the sliced inverse regression approach and does not affect the economic interpretation of the relationship between the exogenous and the endogenous variables.

Table 2.5   **Results: Constrained inverse regression**

| | Dimension-reduced shifter | | | | | |
| | Demand | | Supply | | Marginal cost | |
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
FERT	0.00		0.22	3.81**	0.00	
FUEL	0.00		0.14	3.35**	0.00	
HLB	0.00		0.71	7.02**	0.00	
POL	0.00		–0.17	–0.59	0.00	
RHW	0.00		0.00		–0.88	–3.46**
GAS	0.00		0.00		–0.28	–3.28**
TPI	0.00		0.00		–0.79	–3.92**
IR	0.00		0.00		–0.48	–2.82**
USPOP	0.03	3.16**	0.00		0.00	
USINC	0.03	0.30	0.00		0.00	
WGHT	1.96	9.95**	0.00		0.85	5.16**
PRTN	–0.18	–0.74	0.00		–0.63	–3.82**
CAUC	167.78	12.32**	0.00		0.00	
JINC	0.19	20.49**	0.00		0.00	
KANS	0.95	3.79**	–0.43	–1.67	–1.04	–5.19**

Notes: See table 2.2 for explanation of abbreviations. KANS = Kansas City dummy variable.

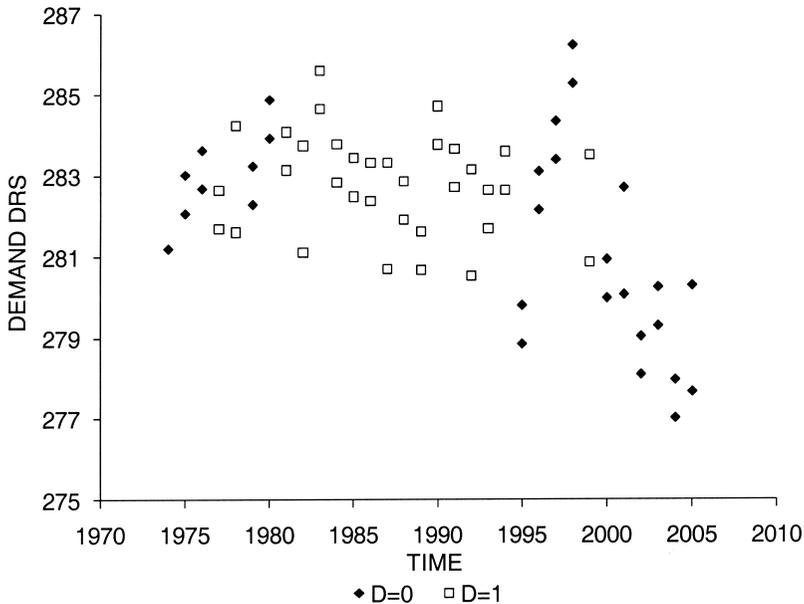**Significant at 5 percent level.

Fig. 2.10   **Realizations of the constrained inverse regression (CIR) demand dimension-reduced shifter: 1974–2005, binding and nonbinding policy years**
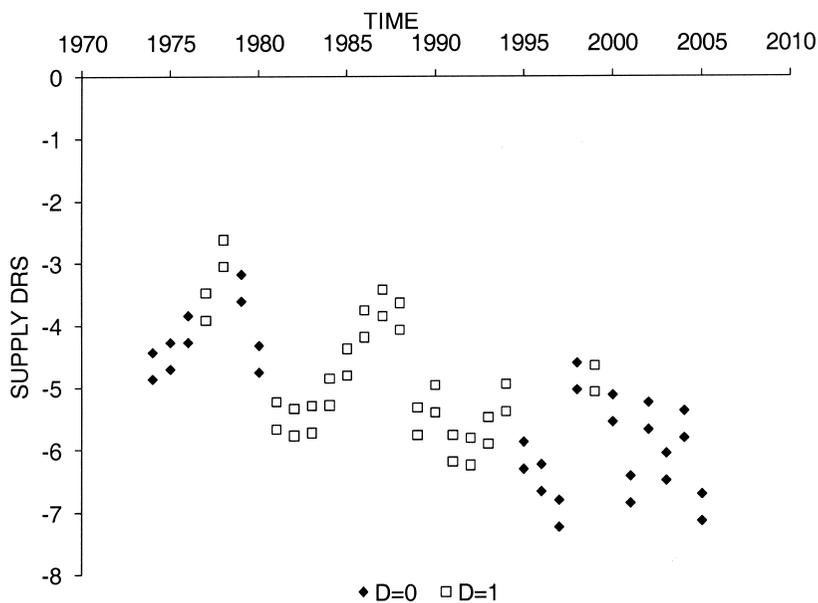
Fig. 2.11 Realizations of the constrained inverse regression (CIR) wheat supply dimension-reduced shifter: 1974–2005, binding and nonbinding policy years
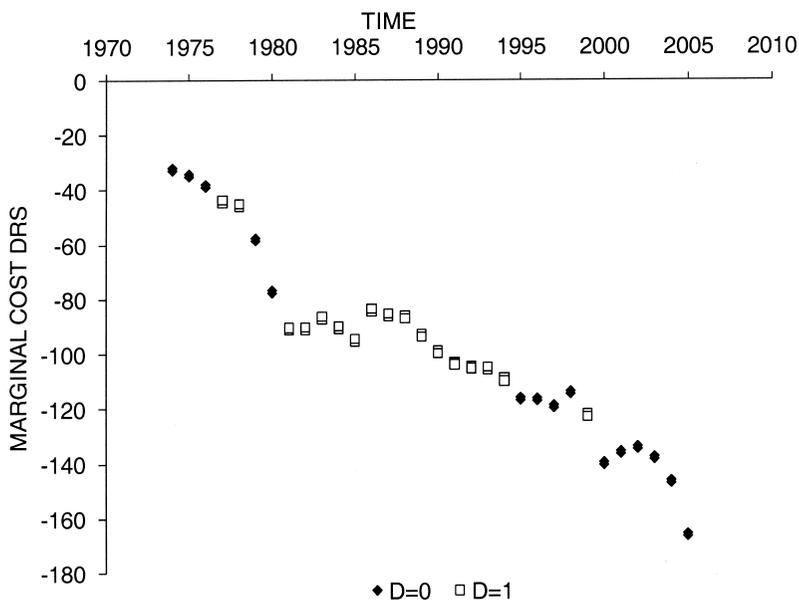

Fig. 2.12 Realizations of the constrained inverse regression (CIR) processor non-wheat marginal cost dimension-reduced shifter: 1974–2005, binding and nonbinding policy years
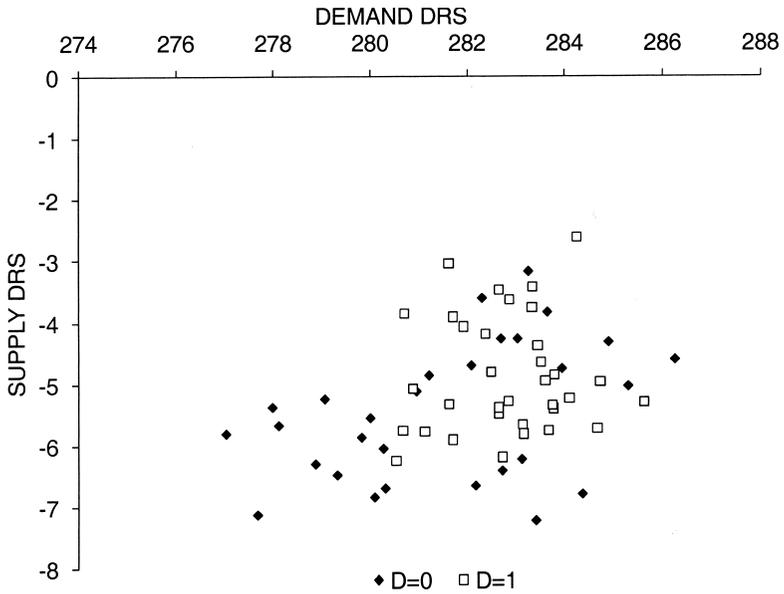
Fig. 2.13 Constrained inverse regression (CIR) demand and supply dimension-reduced shifters (DRS): binding and nonbinding policy years
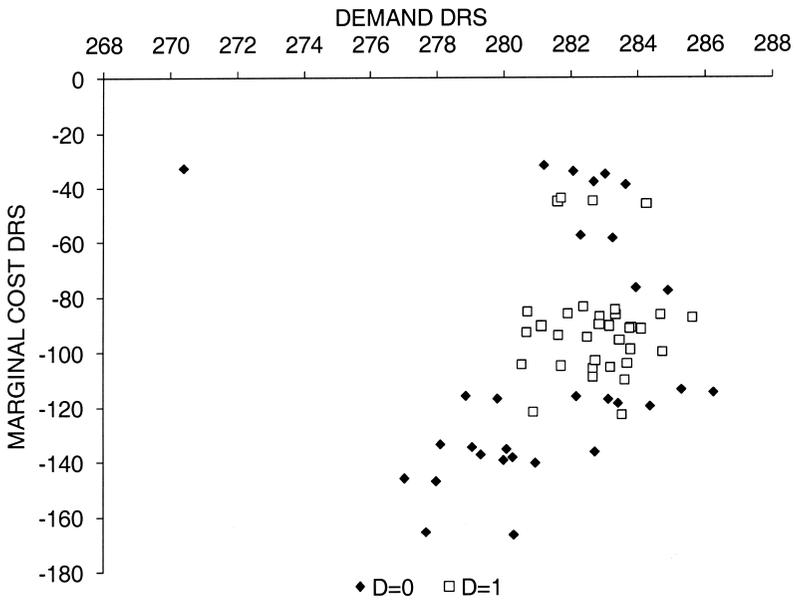

Fig. 2.14 Constrained inverse regression (CIR) demand and marginal cost dimension-reduced shifters (DRS) binding and nonbinding policy years

as the supply DRS realization increases in a partial equilibrium depiction of the market, the price will fall and the quantity produced and consumed will increase as the supply curve shifts out. If the target price was constant, then binding years should be associated with high realizations of the supply DRS for a given realization of the demand DRS. This pattern does not appear in figure 2.13. Figure 2.14 plots annual values of the demand and marginal cost DRS. This figure does not demonstrate any predictable pattern between the relationship between the two DRSs and whether the policy is binding. Consistent with figures 2.10 to 2.12, figures 2.13 and 2.14 indicate that high target prices are a more important determinant of the policy regime than market conditions are.

2.6.2   Comparison of SIR and CIR Results

There are differences in which variables have significant coefficients between the SIR and the CIR estimations. Two variables that were significant in the CIR demand DRS, U.S. population and Japanese per capita income, were not significant in either SIR factor. Manufacturing wage was not significant in either SIR factor, although it was significant in the CIR processing marginal cost DRS. The most important difference was that the policy price has an insignificant effect on the farmer supply DRS in the CIR results, although it had significant coefficients in both SIR factors.

2.7   NW Nonparametric Estimation Results

The second step of the procedure uses the SIR factors and the CIR DRS as regressors in a Nadaraya-Watson kernel estimator of the price margin with a cross-validation bandwidth. This step defines the link function and allows us to compute the conditional mean of the millers' margin.

2.7.1   SIR Factors

Figures 2.15 and 2.16 plot how each factor affects the flour-wheat price margin for binding and nonbinding policy years. In figure 2.15, the price margin is always higher when the policy is binding than when it is not, regardless of the realization of the first factor. The level of the margin is virtually constant for the nonbinding policy regime, regardless of the level of the factor. The level of the margin first increases, then decreases for the binding policy regime as the factor increases. There is no consistent change in the difference in the margins as a function of the level of the factor.

In figure 2.16, the price margin is always higher when the policy is binding than when it is not, except for very high realizations of the second factor. Because only observations for nonbinding policy years include very high values of the second factor, the behavior of the two regressions at the very end of the domain is not emphasized. The margin first increases, then decreases as the second factor increases for both the binding and nonbinding
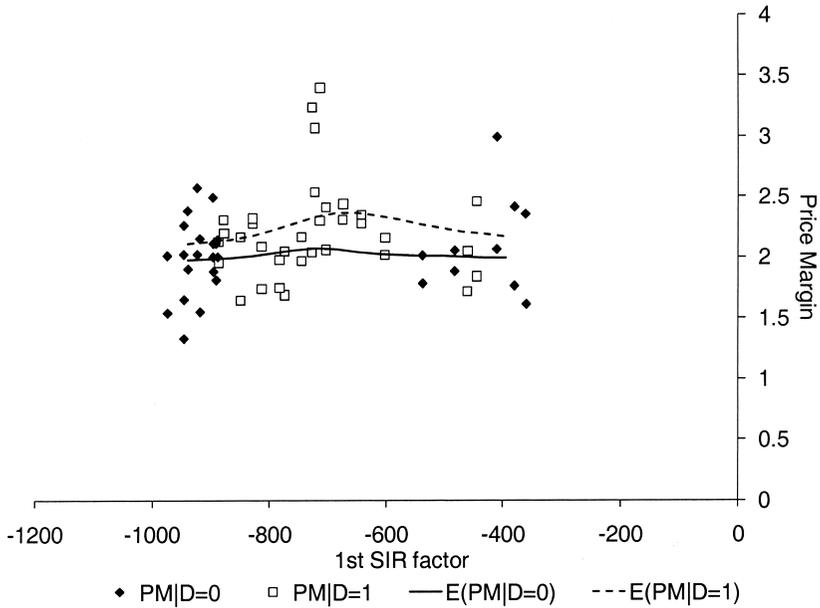
Fig. 2.15   Nadaraya-Watson (NW) nonparametric estimation of the relationship between the flour price-wheat price margin (PM) and the sliced inverse regression (SIR) first factor
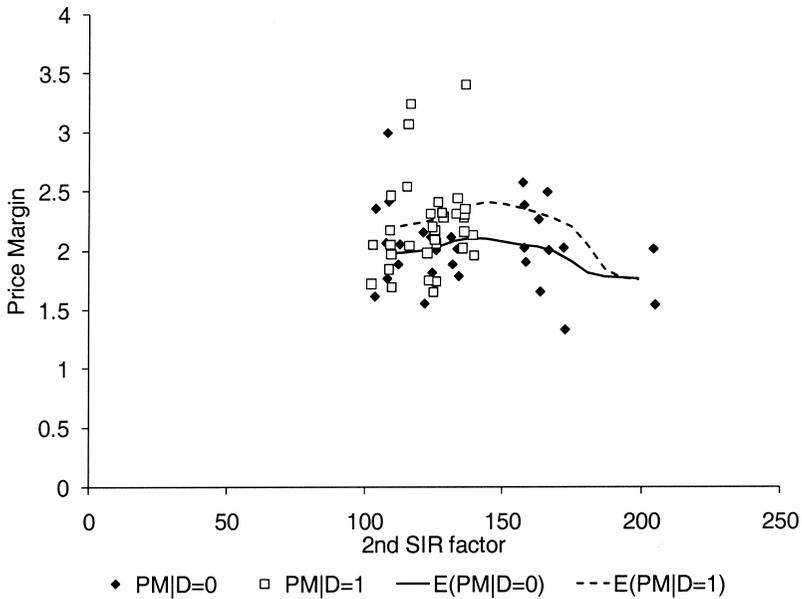

Fig. 2.16   Nadaraya-Watson (NW) nonparametric estimation of the relationship between the flour price-wheat price margin (PM) and the sliced inverse regression (SIR) second factor

policy regimes. The difference between the two margins remains relatively constant until the right-hand end of the domain.

The conditional mean of the millers' margin is $2.07 per hundredweight of wheat when the policy is not binding and $2.31 when it is binding. The $0.24 per hundredweight difference is highly statistically significant, with a *t*-statistic of 3.398 obtained via bootstrapping.

2.7.2   CIR DRS

Figures 2.17 to 2.19 plot how the reduced-form demand, processor marginal cost, and wheat supply DRS affect the flour-wheat price margin. Figure 2.17 addresses demand. The estimated magnitude of the price margin depends on program status. For any given value of the demand DRS, the flour-wheat price margin is larger when the program is binding than when it is not. For both the binding and nonbinding policy regimes, the margin first increases with the demand DRS, then decreases. In both cases, the absolute values of the changes are small.

Figure 2.18 evaluates the effect of processors' marginal cost on the price margin. The observations for both regime types are clustered with respect to the realized values of the processor marginal cost DRS, with the nonbinding years at the extreme values of the DRS and the binding years in the middle. This pattern suggests caution when interpreting the results.
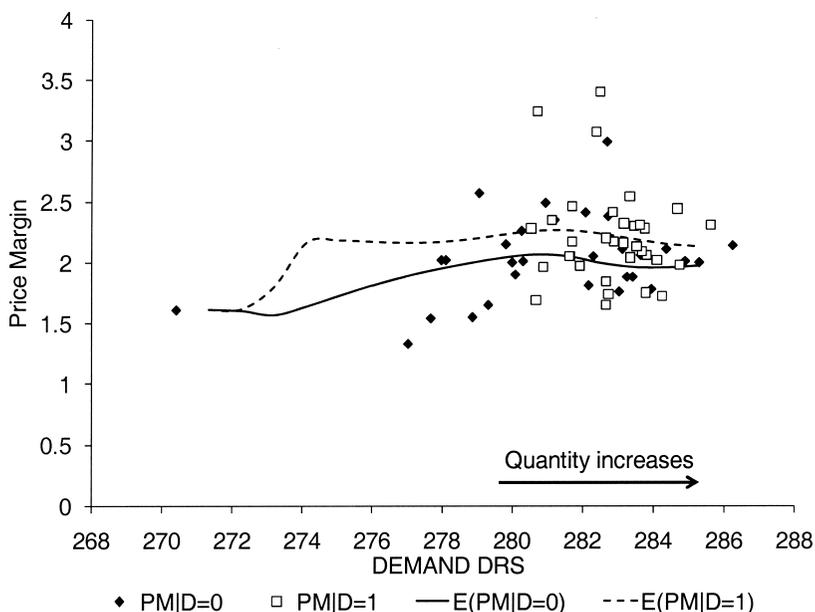

Fig. 2.17   Nadaraya-Watson (NW) nonparametric estimation of the relationship between the flour price-wheat price margin (PM) and the dimension-reduced shifters (DRS) for demand
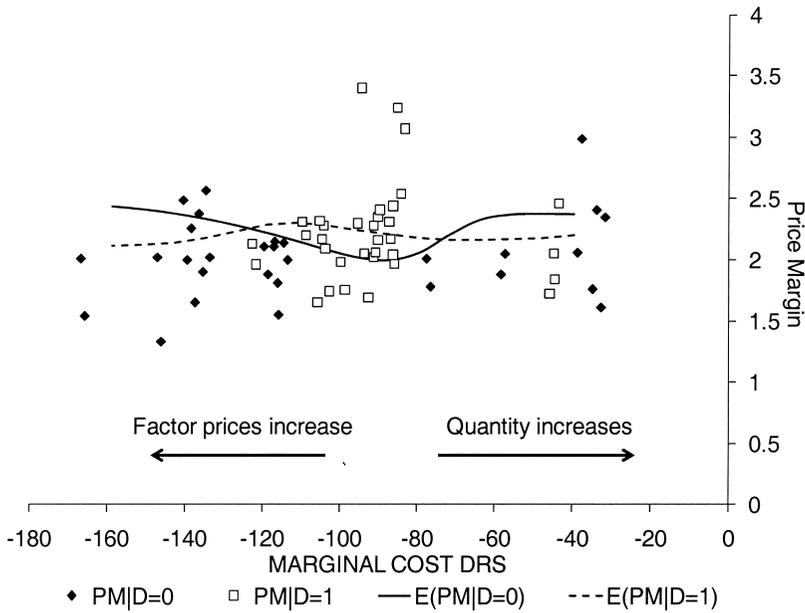
Fig. 2.18 **Nadaraya-Watson (NW) nonparametric estimation of the relationship between the flour-wheat price margin (PM) and the dimension-reduced shifters (DRS) for processor marginal cost**

There are differences between the binding policy and nonbinding policy regimes. In the middle of the range, the price margin is higher for a given realization of the marginal cost DRS when the policy is binding, but the opposite is true on the extremes. When the policy is binding, the price margin is virtually constant across values of the marginal cost DRS. When it is not binding, the price margin first declines as input prices decline and quantity increases, then increases. Thus, for low realizations of the marginal cost DRS when the policy is not binding, the result is consistent with Brorsen et al. (1985), who found that an increase in milling costs increases the flour-wheat price margin on a one-for-one basis. However, for high realizations of the marginal cost DRS when the policy is not binding and for all realizations when it is binding, the outcome is not consistent with Brorsen et al. (1985). Regarding the primary research question, the results are consistent with the possibility that a change in policy regime triggers a change in pricing behavior. For years when the policy is binding, millers appear to absorb as least as large of a share of a marginal cost increase as they do in years when the policy is not binding.

Figure 2.19 evaluates the effect of farmers' DRS of wheat supply on the price margin. As supply shifts out, the price margin first increases and then decreases in years when the policy is binding. In years when payments are not
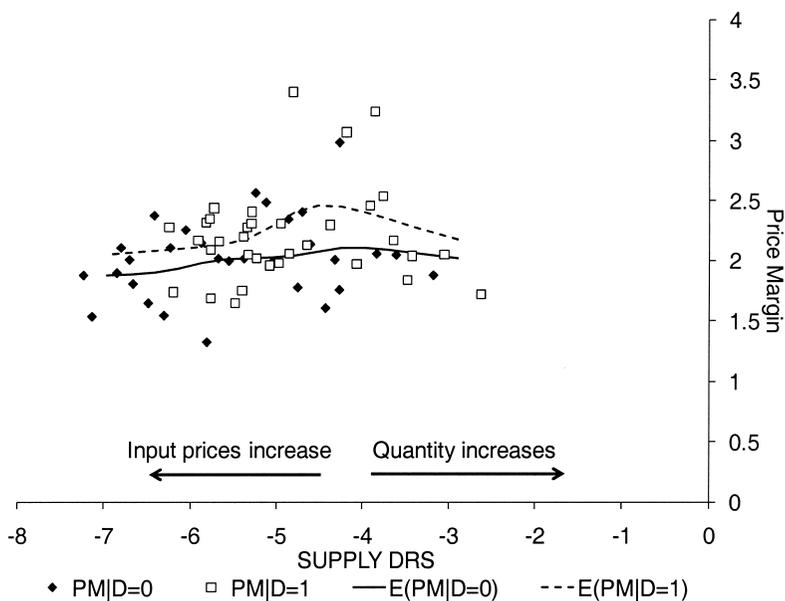
Fig. 2.19   Nadaraya-Watson (NW) nonparametric estimation of the relationship between the flour price-wheat price margin (PM) and the dimension-reduced shifters (DRS) for wheat supply

made, the price margin follows the same general pattern, although it is much less responsive to changes in the supply DRS. These policy-dependent relationships between supply and the price margin suggest that millers' strategies differ depending on whether the policy is binding.

The restricted model generates a conditional expectation of the millers' margin of $2.02 per hundredweight of wheat when the policy is not binding and $2.25 when it is binding. The $0.23 per hundredweight difference is statistically significant, with a *t*-statistic of 2.5701 obtained via bootstrapping.

2.7.3   Implications

Overall, the analysis of the patterns obtained from the SIR-NW algorithm suggests that the data are consistent with a simple static model of market power. The figures suggest that millers are able to impose higher price margins in years in which the policy is binding. When payments are made, farmers respond to the target price and are less likely to store their grain and wait for a higher price to be offered by buyers. This circumstance allows millers to exploit market power and reduce the price of wheat relative to the price of flour.

The results of the two models differed in one important respect: the policy price was a significant explanatory variable for both SIR factors but was

insignificant in the estimate of the supply DRS in the CIR model. Even though the two models varied in terms of which variables were significant, there was very little difference in the results regarding the research question of interest: whether the flour-wheat price margin is affected by the policy regime and, if so, by how much. The results of the two models were consistent regarding the difference in millers' marketing margins in binding and nonbinding policy years. The NW analyses based on both models indicate that the margins were higher in binding policy years regardless of the realizations of the shifters and DRS, respectively. That is, the higher margin found in binding policy years is not due to characteristics of demand, supply, or processor marginal costs in those years. In both models, margins were about 10 percent higher in binding years, and the hypothesis that the difference in the margins was not statistically significant was rejected.

2.8   Conclusion

As a sector, agriculture is subject to a great deal of government intervention. Although expenditures have declined substantially in the past decade due in part to international trade negotiations, in the last three years, Commodity Credit Corporation total net outlays for commodity programs have ranged between $9 and $13 billion, depending on economic conditions. For wheat alone, net outlays ranged between $0.7 and $1.2 billion (USDA 2010). Given the magnitude of these expenditures, there is an obvious public interest in efficient policy measures and the beneficiaries of these measures.

This analysis demonstrates that market power might redistribute the benefits of government intervention. It provides empirical evidence that U.S. wheat millers were able to increase their marketing margins, on average, by approximately 10 percent when farmers received payments through a marketing loan program. This expected increase in margins was computed controlling for the realizations of a broad set of supply, demand, and processor marginal costs shifters in those years. In turn, these findings suggest that millers are extracting a rent from the deficiency payment/marketing loan gain policy. Thus, the analysis suggests that the general assumption that competitive models may be a good approximation for imperfectly competitive agricultural markets does not necessarily hold, particularly if distribution, as well as efficiency, is a concern.

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