NOSTALGIC DEMAND

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This paper attempts to understand demand for local and other nostalgic production in food. In U.S. household scanner data, nostalgically produced foods sell for a large premium. Controlling for income and demographics, experts who work in food production and health are no less likely to purchase nostalgic milk and eggs, but are less likely to purchase local eggs in regions where eggs are produced at scale. In a choice experiment, willingness to pay for local tomatoes decreases when quality is shown. A simple theory explains this puzzling demand. When goods have too many dimensions of quality to communicate in market exchange (the USDA records over 70 for milk), innovation has ambiguous effects, consumers seek nostalgic signals of quality, and straightforward policies can backfire.

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1 Introduction

The average U.S. acre of corn yielded seven times more grain in 2017 than in 1935. The average cow produced more than twice as much milk in 2004 as in 1970. And the average hen laid 2.3 times more eggs in 2004 than in 1925 (NASS; USDA ERS, 2005, 2006).

These improvements have come through two innovations. On farm innovations increased the total value of U.S. agricultural production by 133% from 1880-1997 (Costinot and Donaldson 2016; not including 1921-1953). And transportation innovations have made it feasible to produce goods in better suited locations; the integration of markets accounted for an additional 178% increase over the same period. This integration also offers consumers a larger variety of produce, both in- and out-of-season.

However, a small but increasing number of consumers demand that food be produced without these innovations: using antiquated technologies, or locally, suggesting that agricultural markets be dis-integrated. Farmers' markets grew in number 180% from 2006-2014, and total local food sales were $6.1b in 2012 (Low et al., 2015). Consumers demand that production be constrained to avoid modern inputs (organic, antibiotic free), avoid scale (family farm or small scale), avoid feeding animals new diets that are more calorically efficient (preferring grass or vegetarian fed), or avoid modern production modes (cage free, free range, or pasture raised). And consumers increasingly demand that production be constrained to older, inefficient varieties of crops (preferring varieties that have not been genetically engineered, or heirloom varieties that were rejected by previous generations). 49% of Americans believe that genetically modified foods are worse for health (Pew Research Center, 2018), and non-GMO sales increased to $200b in 2014 (Packaged Facts, 2015).

This represents a puzzle. Advocates claim that it is better to produce food without these innovations. But better how?

Nostalgic production is not substantially better on most observable outcomes. Genetic modification reduces land and pesticide use (Klumper and Qaim, 2014), and there is no substantial observable evidence it generates foods that are less safe (National Academy of Science, 2016). And many of the claims around local production do not stand up to scrutiny. Transportation accounts for only 4% of emissions from food (Weber and Matthews, 2008), and storing local products between seasons can result in higher emissions than importing from better suited climates (Brenton et al., 2009). Local production can also exacerbate economic inequality: farmers located near wealthy consumers are themselves wealthier.

There is an extensive literature that quantifies willingness to pay for individuals labels, mostly using hypothetical valuation (for reviews on organic see Hughner et al. (2007), GMOs: Lusk et al. (2005), local: Feldmann and Hamm (2015)). But this literature treats these attributes as valued per se, and has not resolved *why* consumers demand them. If consumers care about these attributes because they are associated with a particular outcome, why not demand that outcome directly, rather than constrain production to certain vintages or locations? Why would consumers ask that production be local or heirloom, rather than fresh, healthy, or low environmental impact?

Critics conclude that consumers who demand that foods be produced locally or without modern innovations have irrational aversions (Desrochers and Shimizu, 2012). Others attempt contorted explanations: the Annual Review of Nutrition suggests that consumers believe that food that interacts with scientists becomes contaminated under a 'magical law of contagion' (Scott et al., 2017).

In absence of an explanation, market participants take demand for nostalgia as a given. Firms dismantle innovations to meet whatever form of production is in demand. Governments invest in labeling or supply, justified as a response to increased demand. The USDA has spent over \$85m on expanding local production, without coherently articulating why markets should be dis-integrated.[1]

This paper attempts to understand demand for local and other nostalgic production in food. It provides new quantitative evidence and is the first to take seriously a new explanation: consumers do not value these modes of production intrinsically, but unobservables they are associated with. A simple theory shows that in such an environment, seemingly straightforward policy approaches can backfire. To my knowledge, it is the first national analysis of purchases of fringe nostalgic attributes (including local, family farm, grass fed, and non GMO labels).[2]

In the first part of the paper, I document several facts on demand for nostalgic and local production.

First, among Nielsen Homescan consumers, I analyze demand for milk and eggs. I link each product's UPC to an independent database of attributes, which allows me to determine which products are labeled as local, or one of several nostalgic labels: non-GMO, organic, cage free, free range, pasture raised, family farm, and grass fed. Milk and eggs that were produced nostalgically sell for a large premium over standard products (products with an 'organic' label sell for 18-25% more; non-GMO label 46-79% more; 'family farm' 16-31% more; and cage free 60% more) and account for an increasing share of the market (the share of milk and eggs that are organic more than doubled between 2006 and 2016). Local milk sells for a premium but local eggs sell for less.

Second, I analyze the choices of experts, who are likely to make more informed decisions within their domains. Bronnenberg et al. (2015) find that experts are substantially less likely

[1]For example, the department launched a 'Know Your Farmer, Know Your Food' initiative in 2009 to "begin a national conversation to help develop local and regional food systems and spur economic opportunity."

[2]Low and Vogel (2011) and Low et al. (2015) use nationally representative data on farms to analyze supply through local channels.

to purchase national brands of common products. That leads that paper to suggest that there is little difference between national and cheaper store brands of these products, and nonexpert consumers may be making mistakes. I connect my purchase data to the same occupation data, and find that consumers who are health experts (nutritionists, physicians, and nurses) or food production workers are no less likely to purchase nostalgic milk and eggs, controlling for income, college education, and market fixed effects. In particular, these experts are no less likely to purchase non GMO milk or eggs, all else equal.[3] In contrast with Bronnenberg et al. (2015), these results are broadly consistent with these purchases not being mistakes, or being the result of mistakes that are independent of expertise. However, I find that in egg producing regions, where local eggs are produced at scale, experts are differentially less likely to purchase local eggs. This result is not consistent with an intrinsic preference for local production, or local production being valued because consumers have better information about local producers (as in finance, Ivkovic and Weisbenner, 2005). It is consistent with local production representing a different signal in these regions.

Third, I decompose demand for local produce in a choice experiment. Consumers in my nationwide sample are willing to pay more for locally grown tomatoes, suggesting that they do not agree on a relative ranking of the quality of produce. Willingness to pay for a good's origin decreases when attributes of quality are shown, suggesting it is in part a signal of quality.

In the second part of the paper, I develop a simple theory to explain this puzzle. The core of the theory is based on consumer reactions to innovations. Innovations have dramatically lowered costs and improved observable quality. But how has innovation affected hidden dimensions of quality?

Food has many dimensions of quality: as it is ingested, it interacts with the body in complex and subtle ways. The most commonly used nutrient database reported up to 7 components per food item in 1896, 79 in 1996, and 146 in 2011.[4] It is not feasible to communicate all dimensions of quality in market exchange. I define an attribute as *hidden* if it is prohibitively costly for consumers to consider in a choice. The economy may not be aware of the existence of a dimension of quality; or if it is aware, dimensions of quality may be prohibitively costly to measure, communicate, or verify.[5] Firms may not have an incentive to reveal quality or educate consumers (Gabaix and Laibson, 2006). Consumers

[3] Relatedly, opinion surveys by Pew Research Center (2018) find a mixed association between science knowledge and the belief that GMO foods are worse for health. In its 2016 survey, respondents with high science knowledge were more likely to view GMO foods as unsafe than those with low science knowledge (37% vs. 29%), but in its 2018 survey, this result reversed (38% vs. 52%). This study analyzes choice rather than opinion data.

[4] USDA National Nutrient Database for Standard Reference

[5] For example, nuclear magnetic resonance can differentiate organic and conventional tomatoes but would be prohibitively costly for consumers; Hohmann et al., 2014.

may internalize quality only after a lag (e.g., micronutrient deficiency has delayed effects), or have difficulty identifying the utility of a good because multiple factors affect an outcome (cancer, obesity, Alzheimers, and early puberty are functions of many factors).[6]

As a result, consumers infer quality from surprisingly few observables. Some are known at the time of purchase: a consumer buying milk may observe a label and the condition of the carton. After purchase, the consumer experiences its appearance, smell, and taste. Even an extremely informed consumer knows little more about a particular product's quality: he may have memorized a subset of the nutrient profile from a few samples of milk tested in a government lab, and may have internalized some rules of thumb (e.g., some vitamins deteriorate in sunlight) or labels to avoid (imports may have traces of chemicals banned in the U.S.).

In my model, firms implement innovations that reduce production costs, without regard to their effects on hidden quality. If consumers believe that innovations damage hidden dimensions of quality, consumers may seek out nostalgic or local production as signals of hidden quality.

This model produces seven implications consistent with observed features of this demand.

First, consumers are pessimistic about innovation in goods where important dimensions of quality are hidden, such as food. When quality is observable, as in typical models, innovation weakly improves welfare. But when quality is hidden, innovation has ambiguous effects on expected welfare.

Second, when products with hidden quality face innovation, consumers may demand attributes associated with nostalgic production. To be stable, signaling attributes must be differentially costly to produce with innovative technologies. Thus, consumers demand nostalgic processes, rather than futuristic or alternative contemporaneous processes. This explains why the direction of demand tilts towards heirloom varieties rather than genetically engineered superfoods. However, this demand is over the output, not the production process per se. Consumers demand nostalgic food crops, milk, and eggs, but not biofuels, leather, or down, which are nonfood outputs of nearly identical agricultural processes. These latter outputs interact with utility in a far simpler way, and do not have as many hidden dimensions of quality.

Third, demand for nostalgia increases in income: wealthier consumers are willing to pay more for quality.

Fourth, the value of observing a nostalgic production attribute decreases when additional information about quality is shown. Providing information reduces the informativeness of these signals.

Fifth, multiple labels may coexist on the market. The mapping between the form of

[6] Legal systems are ill suited to enforcing dimensions that are hard to measure.

nostalgia and hidden quality is difficult to learn, and consumers may have different beliefs.

Sixth, this behavior appears irrational to observers who consider only observables. To these observers, modern consumers who prefer antiquated production processes appear to violate the weak axiom of revealed preference.

Seventh, this demand can follow faddish shifts. Once consumers update their beliefs, lower quality producers may mimic valued signals, and so destroy their value. As fringe attributes gain popularity and supply adjusts, consumers seek out new attributes from the fringes. Markets may take time to equilibrate, or may not equilibrate at all. For example, a metaanalysis finds that preference for locally produced food was weak and in some cases negative in the 1980s, but reversed and became stronger than that of organic in the late 2000s (Adams and Salois, 2010).

While other simple theories can each explain a small number of these features, I am not aware of an alternate theory that can explain all. Status signaling can also generate demand for arbitrary attributes (Pesendorfer, 1995), but there is more demand for these attributes in groceries, which are consumed in private, than in more visible outputs from similar production processes, like clothing.

Under this model, there are two substantial implications for policy.

First, seemingly straightforward policies can backfire. A common response to increased demand is to remove frictions to reduce the cost of nostalgic production. This can undermine demand and in some cases lower welfare. In this model, consumers do not care about nostalgic production per se, and what they do care about is lost if nostalgic products are produced at lower cost. Producing desired attributes with innovative technologies can induce the market to switch to costlier and more eccentric signals. For example, it may be that integrating the supply of organic products through national certification contributed to the emergence of demand for local production.

Second, it suggests a productive potential avenue for policy. There are tentative links between innovation in food processing and the rise of obesity (Cutler et al., 2003) (in 1980, 15% of Americans were obese; in 2000, 31% were (Flegal et al., 2002)). This paper illuminates one channel through which innovation can lead to deterioration in the healthfulness of food. In response to this concern, portions of the food sector have begun dismantling innovations. However, if consumers dislike potential side effects of innovation, rather than innovation per se, it may be possible to redirect rather than dismantle innovation.

The next section analyzes demand for nostalgic production in a nationally representative sample of purchases. Section 3 analyzes demand for product origin in an online choice experiment. Section 4 develops a model of nostalgic demand. Section 5 concludes.

2 Who buys nostalgically produced food?

I analyze demand for two simple agricultural products, eggs and milk, which have three key features. First, different products can be distinguished by UPCs. Second, different products are increasingly marketed with variety of attributes, including organic, local, non-GMO, family farm, grass fed (milk), and cage free, free range, and pasture raised (eggs). Third, they appear otherwise relatively undifferentiated, so differences in choice are less likely to arise from differences in horizontal preferences.

Eggs and milk have seen profound process innovations over the past century. Hens require Vitamin D, and as a result historically required access to the outdoors to survive. This limited the scale of poultry farms. After the discovery of Vitamin D in 1922, and its subsequent synthesis, it became possible to maintain hens indoors year round by supplementing their feed. This innovation, together with innovations in housing and processing, allowed egg farms to scale, to thousands of hens by the 1950s, and millions of hens by the 1970s.[7] The entire production function has been carefully tuned: modern egg farms incorporate automated egg washers, blood spot detectors, slatted floors that discourage brooding, and feed supplemented with the amino acids that hens would typically get from foraging insects. These changes have increased production volumes: in 1925 each hen laid an average of 112 eggs per year; in 2004 each hen laid an average of 260 eggs (USDA ERS, 2006). Egg production is geographically concentrated: modern egg farms operate at large scale and transport their products to other regions (Iowa in particular accounts for about 20% of U.S. egg production). In some markets in the midwest, over 80% of purchased eggs are labeled local (see Appendix Figure A1a for a map). Milk production has also changed, with mechanization and a switch from obtaining food from pasture and foraging to being fed grain. Milk production per cow more than doubled from 1970 to 2004 (USDA ERS, 2005).[8] However, milk production is less geographically concentrated (see Appendix Figure A1b).

However, both milk and eggs have many dimensions of quality, including over 100 for eggs and 70 nutrients for milk reported by the USDA.[9] While egg and milk cartons include nutrition facts labels, these values contain a small fraction of these nutrients and are typically imputed. Many dimensions of quality are hidden.

2.1 Data

I combine data from three sources:

[7] The US Agricultural Census reported that in 2012, 77% of laying hens were in farms with over 100,000 hens.

[8] Comparing milk production per cow in 1970 in the US to milk production per cow in 23 major states in 2004. Overall trends are consistent with production being comparable in these two populations.

[9] USDA National Nutrient Database for Standard Reference

I use Nielsen Homescan (HS) data on purchases among their panel of respondents from 2011-2016. Respondents place a barcode scanner at home, and scan each item purchased. The panel is selected with an aim towards representing U.S. consumers, and supplies sample weights for each household.[10] This Nielsen data includes attributes of each product, including brand, size, whether it is organic, and for eggs, whether they are cage free. I assume that a given UPC is organic or cage free if it was marked so in any year. This data omits products that do not have UPCs, which may include some goods purchased at farmers' markets. If farmers' market purchases are correlated with purchases of nostalgic UPCs, my main occupation results may underestimate the difference in behavior between experts and other consumers.

I link UPCs to a database collected by Label Insight to obtain additional attributes (free range, pasture raised, vegetarian fed, grass fed, and whether the label indicates it is local or from a family farm).[11] Because this database was constructed in 2017, it offers only coverage of UPCs in recent use. My main analysis focuses on the most recent year of purchases (2016), which has the highest match rate: UPCs with a match in Label Insight account for 52% of eggs and 61% of milk volume purchased by Homescan respondents. I use this matched sample of UPCs when analyzing attributes present only in Label Insight.

I link the purchase data to two PanelViews surveys administered to panelists by Bronnenberg et al. (2015) (in September 2008 and October 2011). Both surveys ask for the respondent's occupation, classified according to the 2002 Bureau of Labor Statistics codes. I use each respondent's most recently reported occupation. Analyses that include these variables will restrict to the set of panelists who were active in both 2011 and 2016.

2.2 Descriptives

Nostalgic and local products sell for a large premium

Table 1 shows a hedonic price decomposition of products possessing different attributes sold in 2016. The average price for a standard half gallon of milk was $2.09, and for a standard dozen eggs $1.99. All nostalgic labels except local eggs sell at higher prices. Local milk sells for $0.17 more; local eggs sell for $0.90 less. Organic products sell for $0.38 (milk) and $0.51 (eggs) more; products with a family farm label sell for $0.32 (milk) and $0.62 (eggs) more; non GMO $1.65 (milk) and $0.91 (eggs). Milk from grass fed cows sells for $0.91 more. Eggs that are cage free sell for $1.20 more; free range $0.34 more; pasture raised $0.61 more. These equilibrium prices may represent differences in a combination of supply

[10] For more information on how the data compares to consumption diaries, see Zhen et al. (2009).

[11] I retrieve data on all eggs on the platform on June 22 and milk on June 27, 2017. Data is copyright of Label Insight (http://www.labelinsight.com) and used per agreement; see disclaimer at end of paper.

and demand.

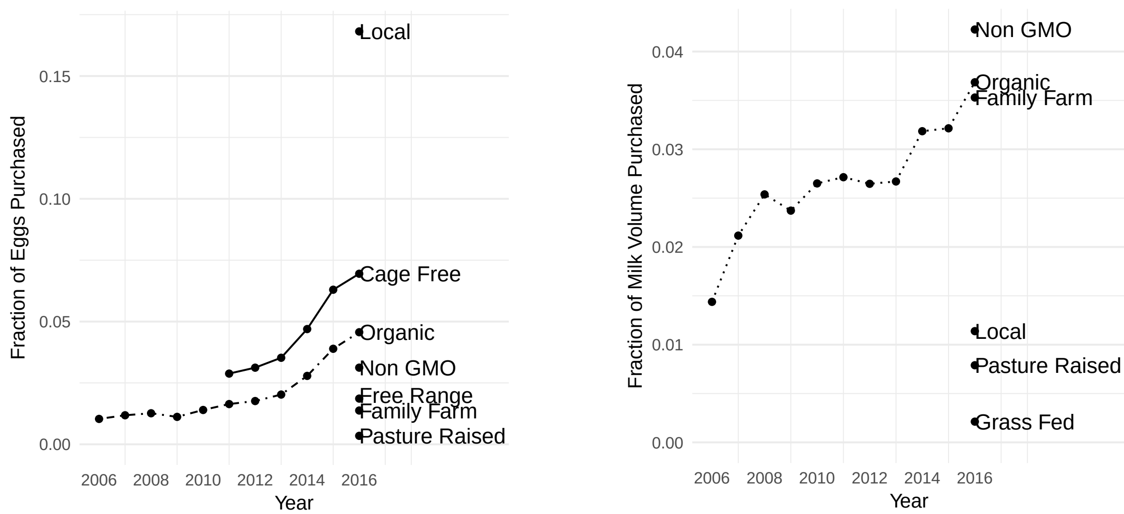
Table 1: Price Decomposition (Hedonic) 2016

	Milk	Eggs
	(1)	(2)
Constant	2.091***	1.991***
	(0.002)	(0.002)
Local	0.168***	−0.904***
	(0.011)	(0.004)
Nostalgic:		
Organic	0.381***	0.507***
	(0.048)	(0.022)
Family Farm	0.324***	0.622***
	(0.007)	(0.018)
Non GMO	1.647***	0.914***
	(0.048)	(0.023)
Grass Fed	0.914***	
	(0.051)	
Cage Free		1.203***
		(0.007)
Pasture Raised		0.613***
		(0.026)
Free Range		0.335***
		(0.015)
Sample	LI UPCs	LI UPCs
N	215,116	254,584
R^2	0.494	0.454

Notes: ***Significant at the 1 percent level.
Outcome is net price for single packages of dozen eggs and half gallons of milk ($).
Unit of observation is a purchase. Standard errors in parentheses.

Figure 1: Trend in Purchases by Attribute

(a) Eggs (b) Milk



Fraction of eggs and milk volume (fluid ounces) purchased by Nielsen Homescan panelists in the given year. Label Insight measures are reported only for the most recent year which has the highest overlap with the products in the Homescan sample.

Nostalgic production accounts for an increasing share of the market

These attributes account for an increasing fraction of eggs and milk volume sold. Figure 1a shows the increase in the market share of organic eggs, and cage free eggs (starting from 2011 when it is first measured). Figure 1b shows an increasing trend in the market share of organic milk. Both figures also show the fraction of product with more nascent attributes measured from Label Insight in 2016, for the subset of UPCs in that dataset.

2.3 Demand

I next analyze purchases by consumer demographic, following Bronnenberg et al. (2015). This provides suggestive evidence on the extent to which demand for attributes is driven by income, information, or preference.

I consider separately whether a product is labeled local, or has at least one nostalgic label (for all products: organic, non GMO, or family farm; for eggs also cage free, free range, or pasture raised; and for milk also grass fed). For each consumer, I compute the fraction of total product (fluid ounces of milk and number of eggs) that is purchased with a given attribute. I regress this fraction on college education, occupation category, market fixed effects, income quartile fixed effects, and other demographics (household composition, and age, race, and gender of household head). I focus on three occupational categories that are likely to reflect different expertise about food and nutrition. Health experts (including physicians, nurses, and nutritionists) are likely to better understand how food choices affect health, and potentially have preferences for health. Food production workers are likely to have better information about production choices. Food preparation and serving workers (including chefs) are likely to have better information, or preferences for, taste and other observable dimensions of quality.[12]

Regression results are shown in Tables 2 and 3. I consider first purchases that have any nostalgic attribute, and then local. Within each set of attributes, the first two columns include all 2016 Nielsen respondents who have purchased at least one product in the Label Insight database. The third column restricts to the sample of respondents who participated in the 2008 or 2011 PanelViews surveys, and adds occupation category. For eggs, I compute two additional columns which consider how demand for origin differs in egg producing regions.

I find:

Higher income households are more likely to purchase nostalgic milk and eggs. They are less likely to purchase local eggs.

Households in the highest quartile of income (earning above $100,000 per year) are more likely to purchase nostalgic milk and eggs. In the full sample they are more likely to purchase local milk; this effect becomes insignificant when occupation category is controlled for. They are less likely to purchase local eggs. This combined with the price results suggests that local eggs with UPCs may be lower quality on average (results could differ for eggs marketed without UPCs, such as many sold through farmers' markets, which are not in my data).

Food production and health experts are no less likely to purchase many types of nostalgic milk and eggs. Food preparation and serving workers are less likely to purchase nostalgic milk.

I consider purchases by occupation, holding fixed income, college education, demographics, and market fixed effects:

- Food production workers are statistically significantly more likely to purchase local eggs. They are also more likely to purchase nostalgic milk with a coefficient that is 1.3 times the magnitude of that of being in the highest income quartile, and nostalgic eggs with a coefficient 36% of the magnitude of being in the highest income quartile, though these results are not statistically significant.

[12] See Appendix A for more information.

- Health professionals are statistically significantly more likely to purchase local milk, with a coefficient that is larger than the magnitude of being in the highest income quartile. They are also more likely to purchase nostalgic eggs, with a coefficient that is 64% of the magnitude of that of the highest income quartile, though this result is not statistically significant.
- Food preparation and serving workers are less likely to purchase nostalgic milk

Table 2: Milk Purchases 2016

	Nostalgic Label					Local
	(1)	(2)	(3)	(4)	(5)	(6)
CollegeEducated	0.019***	0.017***	0.005	0.0001	−0.0004	0.001
	(0.002)	(0.002)	(0.004)	(0.001)	(0.001)	(0.002)
Income[40-60)	0.002	0.002	−0.011**	0.002**	0.002**	−0.003
	(0.003)	(0.003)	(0.006)	(0.001)	(0.001)	(0.002)
Income[60-100)	0.017***	0.016***	0.002	0.003***	0.003***	−0.002
	(0.003)	(0.003)	(0.005)	(0.001)	(0.001)	(0.002)
Income[100,)	0.054***	0.051***	0.036***	0.010***	0.008***	0.0004
	(0.003)	(0.003)	(0.006)	(0.001)	(0.001)	(0.002)
OFood Prep/Serving			−0.029*			−0.008
			(0.016)			(0.006)
OFood Production			0.047			−0.006
			(0.038)			(0.014)
OHealth Profession			0.0004			0.016*
			(0.027)			(0.010)
Market fixed effects?		X	X		X	X
Demographic controls?	X	X	X	X	X	X
Mean of dep. variable	0.065	0.065	0.062	0.012	0.012	0.010
Sample	All LI UPCs	All LI UPCs	Surveyed LI UPCs	All LI UPCs	All LI UPCs	Surveyed LI UPCs
N	51,414	51,414	13,185	51,414	51,414	13,185
R^2	0.023	0.065	0.101	0.006	0.067	0.086
Adjusted R^2	0.023	0.061	0.085	0.006	0.063	0.071

Notes:
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
Dependent variable is fraction of total milk volume purchases with given attribute. Standard errors in parentheses.
Household income reported in thousands of dollars; omitted category is household incomes below $40,000.
Demographic controls include household composition, presence of children, and household head's race, gender, and age.

In egg producing regions, experts are less likely to purchase local eggs

In regions with high production, local eggs are likely produced at scale, not with nostalgic technologies. I define a region (DMA) as 'egg producing' if at least 40% of purchased eggs are labeled local. These regions include approximately 10% of the consumers I observe. Columns 7 and 8 of Table 3 interact my household characteristics of interest with an indicator for whether the household lives in an egg producing region. I find that all food and health experts are less likely to purchase local eggs in these region, substantially so for health and food production workers but with a non significant result for food preparation and serving workers.

Table 3: Egg Purchases 2016

	Nostalgic Label			Local				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CollegeEducated	0.035***	0.032***	0.013***	0.005	0.004	−0.004	0.008***	−0.007
	(0.002)	(0.002)	(0.005)	(0.003)	(0.003)	(0.006)	(0.003)	(0.006)
Income[40-60)	0.010***	0.008**	−0.008	0.001	−0.005	0.003	0.004	−0.010
	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.008)	(0.004)	(0.009)
Income[60-100)	0.033***	0.031***	0.010*	−0.032***	−0.034***	−0.032***	−0.023***	−0.023***
	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.008)	(0.004)	(0.008)
Income[100,)	0.065***	0.061***	0.044***	−0.063***	−0.058***	−0.059***	−0.047***	−0.064***
	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.008)	(0.004)	(0.009)
OFood Prep/Serving			−0.0001			−0.018		−0.017
			(0.020)			(0.025)		(0.028)
OFood Production			0.016			0.206***		0.298***
			(0.038)			(0.049)		(0.053)
OHealth Profession			0.028			−0.031		0.001
			(0.026)			(0.033)		(0.035)
Egg producing region:CollegeEducated							−0.025***	0.018
							(0.009)	(0.018)
Egg producing region:Income[40-60)							−0.079***	0.090***
							(0.012)	(0.023)
Egg producing region:Income[60-100)							−0.097***	−0.058***
							(0.011)	(0.022)
Egg producing region:Income[100,)							−0.099***	0.048**
							(0.012)	(0.023)
Egg producing region:OFood Prep/Serving								−0.027
								(0.068)
Egg producing region:OFood Production								−0.640***
								(0.148)
Egg producing region:OHealth Profession								−0.253**
								(0.102)
Market fixed effects?		X	X		X	X	X	X
Demographic controls?	X	X	X	X	X	X	X	X
Mean of dep. variable	0.092	0.092	0.081	0.153	0.153	0.170	0.153	0.170
Sample	All LI UPCs	All LI UPCs	Surveyed LI UPCs	All LI UPCs	All LI UPCs	Surveyed LI UPCs	All LI UPCs	Surveyed LI UPCs
N	48,316	48,316	12,394	48,316	48,316	12,394	48,316	12,394
R^2	0.036	0.075	0.096	0.013	0.216	0.256	0.218	0.261
Adjusted R^2	0.035	0.071	0.080	0.013	0.212	0.243	0.215	0.247

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
Dependent variable is fraction of total egg purchases with given attribute. Standard errors in parentheses.
Household income reported in thousands of dollars; omitted category is household incomes below $40,000.
Demographic controls include household composition, presence of children, and household head's race, gender, and age.

Occupational differences could arise for several reasons. To the extent that food preparation and serving workers differentially value taste or observable quality, these results are consistent with these products being less differentiated along those dimensions. Food production workers may be better informed about the impact of different production choices. Health experts may have different preferences or information about how food affects health. (Dayoub and Jena (2015) find that health professionals have lower rates of smoking, sedentary activity, obesity, diabetes, hypertension, and coronary artery disease, though their results do not control for income.)

These results stand in contrast to Bronnenberg et al. (2015). That paper finds that these expert consumers are substantially less likely to pay extra for national brand products, suggesting national brands offer little quality difference over store brands.[13] Similarly, I find that food preparation and serving workers are less likely to pay extra for nostalgic milk, and that all experts are less likely to purchase local eggs in producing areas. But I find that food production workers and health professionals are otherwise at least as likely to purchase nostalgic and local milk or eggs as other consumers. These patterns hold for each nostalgic label individually, as shown in Appendix Tables A1 and A2, and results for each label are similar.[14]

In particular, food production and health experts are no less likely to purchase non GMO eggs and milk. This relates to opinion surveys by Pew Research Center (2018) which find a mixed association between science knowledge and the belief that GMO foods are worse for health. In its 2016 survey, respondents with high science knowledge were more likely to view GMO foods as unsafe than those with low science knowledge (37% vs. 29%), but in its 2018 survey, this result reversed (38% vs. 52%). It is unclear if those surveys capture a shift in beliefs or are due to noise in opinion measures.[15]

A difference in health but not taste would be consistent with scientific evidence: Srednicka-Tober et al. (2016) find in a meta analysis that organic milk has a more healthful fatty acid profile; Croissant et al. (2007) echo this nutritional result for pasture raised cows but find that consumers cannot differentiate the taste of milk from conventional and pasture raised cows.[16]

[13]That paper studies a superset of the consumers I observe in my data, since it does not restrict to those who continue with Homescan in 2016.

[14]Food preparation and serving workers are less likely to purchase family farm milk, and cage free eggs. They are more likely to purchase family farm, non GMO, and free range eggs. Food production workers are more likely to purchase local eggs. Health professionals are more likely to purchase local milk.

[15]While National Academy of Science (2016) concludes that there is no substantial observable evidence that genetically modified foods are less safe, it also notes that any new food "may have some subtle favorable or adverse health effects that are not detected even with careful scrutiny and that health effects can develop over time."

[16]Since nutrition labels show a subset of nutrients and in most cases are imputed, such differences would not be visible to consumers.

2.4 Robustness

Appendix Tables A3 and A4 compare results between purchases among the full sample of UPCs and the Label Insight sample for the attributes that are available in both (organic and cage free). Regressions for those individual attributes are similar except for demand for organic among food preparation and serving workers.

While fine occupational categories are available only for the PanelViews subset of respondents, Nielsen also collects coarse occupational categories for the full sample of respondents. These categories include farmers, who are likely to be knowledgable about agricultural production. In Appendix Tables A5 and A6, I find that farmers are no less likely to purchase nostalgic and local milk and eggs. (These results do not include any home production that lacks UPCs.)

To better understand what drives preferences for nostalgic production, I run an online choice experiment to decompose demand for the origin of food.

3 Choice experiment

In actual goods, attributes are correlated, which makes it difficult to identify what drives demand for a particular attribute. I conducted a web-based choice experiment where attributes are varied randomly. Since I am able to control for attributes, I am not restricted to agricultural products that are relatively undifferentiated as when analyzing observational data. I consider tomatoes, the quality of which has been the source of popular discussion. I focus on one of the most puzzling nostalgic attributes of production: local origin.

3.1 Design

Participants were asked to select between hypothetical tomatoes with different prices and attributes, an extension of the experimental design of Onozaka and Mcfadden (2011). 132 participants were recruited nationwide on Amazon Mechanical Turk. Respondents were from 39 different states; 82% are the primary grocery shopper in their household; and the modal respondent has a bachelor's degree and household income between $30,000-$39,999.

Participants were presented with a sequence of choices; in each, they were asked to choose between two tomatoes with randomly selected attributes. These choices came in two parts; participants were randomly allocated to complete part 1 or 2 first. In part 1, the tomatoes differed based on price and origin (grown locally or in a different state). Attributes were selected at random, so it was equally likely for a local option to cost more or less. In part 2, the tomatoes also differed based on other dimensions. Participants were randomly allocated to either part 2a or 2b. In part 2a, options differed along price, origin, and two vertical attributes that are commonly associated with local production: freshness (harvested yesterday, or 2 weeks ago) and production method (organic or conventional). To test whether results differ simply as a result of adding attributes, part 2b presents options differing along price, origin, and two horizontal attributes: flavor (sweet or tart) and size (cherry or standard size). All combinations of options were equally likely. The order of choices and attributes was randomized. (For details about the experimental design and the demographics of participants, see Appendix B.)

I use participant responses to estimate a discrete choice logit model. For respondent i and choice j, option $l \in S_{ij}$ provides utility $u_{lij} = \alpha' X_l - \beta p_l + \epsilon_{lij}$, for a vector of attributes X_l. Because I am able to randomize prices, I am able to identify the price coefficient β; however, because the sample is small, I do not attempt to estimate interactions between consumer and product characteristics. Given logit errors ϵ_{lij}, the probability of selecting product l in choice j is given by $Pr_{lj} = \frac{\exp(\alpha' X_l - \beta p_l)}{\sum_{l' \in S_{ij}} \exp(\alpha' X_{l'} - \beta p_l)}$. I estimate the parameters of this model using maximum likelihood. I focus on the implied value of each attribute ($\alpha_{attribute}/\beta$).

3.2 Results

Results are shown in Table 4.

Table 4: Experimental Results

	Implied Valuation ($)		
		Part	
Variable	A	B1	B2
Local	0.88	0.51	0.82
	(0.12)	(0.10)	(0.16)
Freshness		0.56	
		(0.12)	
Organic		0.40	
		(0.11)	
Flavor			0.71
			(0.14)
Size			0.51
			(0.13)
Participants	132	58	74
Observations	660	2320	2960

Valuation implied by logit coefficient estimates. Each regression uses the data from the specified part of the experiment. Standard errors in parentheses, computed using the delta method, clustered by participant.

Participants are willing to pay $0.88/lb more for tomatoes grown locally, when they are shown only its origin in part 1. Participants are distributed around the U.S., including states where it is objectively inefficient to grow tomatoes at the time of the survey (in February). This implies that they would not agree on a ranking of the desirability of tomatoes grown in different locations.

In part 2, participants are also shown other attributes, so that these attributes are controlled for. The comparison between part 1 and part 2 reveals the extent to which local label is valued because it signals other attributes. If origin is valued per se, and its value does not depend on other attributes, its value should not change between part 1 and part 2 of the experiment. Alternately, if consumers value origin as a signal of the selected attributes, then its value should drop once those attributes are controlled for. In part 2a, when quality information (freshness and organic) is presented, participants are only willing to pay $0.51/lb more for tomatoes grown locally. This is consistent with the value attached to origin arising partly from signaling these two dimensions of quality. The remainder of the value attached to local could be intrinsic, or could result from signaling other attributes of hidden quality beyond the two I control for here.[17]

In contrast to these results, in part 2a, when horizontal attributes (flavor and size) are also presented, the implied value of origin does not change significantly from part 1 (consumers value local tomatoes $0.82/lb more). This suggests the drop is not an artifact of the experimental design, and that origin is not a signal of these horizontal attributes.

While these choices are hypothetical, the experimental design included features to encourage participants to carefully consider their choices. At the beginning of the survey, consumers were informed that 4 choices would be repeated, but could appear in a different format or order the second time, and told that they would earn a bonus for each choice that they made consistently. This incentivized respondents to make choices carefully, and also provided a measure of consistency (92% of these choices were consistent). While hypothetical choices are known to induce desirability biases, since I compare choices across treatments, hypothetical choices would have to be differentially biased between the different parts of the experiment to bias my estimates.[18]

The next section develops a theory of choice under hidden quality that explains these empirical results.

[17]Consumers value the local label more highly than the organic label, consistent with other recent valuation experiments in the literature.

[18]For more discussion about reliability see Appendix B.

4 A model of nostalgic demand

I first describe behavior in an initial generation prior to modern production innovations (you could consider the first generation of consumers your great grandparent). I then consider a current generation that faces modern innovations, and derive the conditions under which it demands that goods be produced nostalgically. The utility implications of consuming a good are hidden until the end of life.

4.1 Consumers

There are two metaphorical generations, each living for two periods. Each generation has a unit mass of consumers, with unit demand for a good. Consumers purchase the good when they are young, and obtain utility when they are old.[19] Electing not to consume a good provides utility zero.

Consuming a good provides old age utility:

$$u := \frac{1}{\beta}V(\mathbf{z}) - p \tag{1}$$

where $\beta > 0$ represents sensitivity to price (inversely related to income), p denotes price, and the utility provided by a good $V(\mathbf{z})$ is a function of K dimensions of quality. Dimensions of quality may be directly internalized like nutrients or toxins, or indirectly internalized like altruism about the environment.

However, consumers may not observe $\mathbf{z}$: they observe prices and observables $\mathbf{x}$. Young consumers anticipate that a good will provide utility:

$$\frac{1}{\beta}\hat{V}(\mathbf{x}, p) - p \tag{2}$$

given beliefs $\hat{V}(\mathbf{x}, p)$.

4.2 Production

There is an infinite mass of potential producers $j \in J$.

Each firm selects an observable $\mathbf{x}$ and a production process r, which produces a good with quality $\mathbf{z}_r$. Firms face marginal cost $c(\mathbf{z}_r, \mathbf{x})$. While firms know marginal costs, they need not know $\mathbf{z}_r$ or even that any dimensions of quality exist.

[19] The delay between young and old corresponds with the delay in realization of hidden quality, and so may be long or uncertain. For example, cancer may take 30 years to develop but some types of poisoning become apparent more rapidly. An alternate model could allow hiddenness to result from noisy revelation of utility.

Firms are price setters; each firm may offer its good at a menu of prices indexed by $m \in M^j$, $\{p^{jm}\}$. For convenience define firm j's lowest price $p^j = \min_{m \in M^j}\{p^{jm}\}$. Firms supply all consumers who demand their product at this price, earning profits:

$$\pi^j := \sum_{m \in M_j} \left[p^{jm} - c(\mathbf{z}_r, \mathbf{x})\right] Q^{jm} \tag{3}$$

where Q^{jm} is the fraction of consumers purchasing choice jm, $Q^j = \sum_{m \in M_j} Q^{jm}$. If two goods appear identical to consumers, a firm can pay an avoidable infinitesimal placement fee of δ to break the tie in its favor; the payment of such a fee is not observed by consumers.[20] Apart from the placement fee, ties are broken at random.

4.3 Equilibrium

A **partial equilibrium** is given by production choices $\{(r^j, \mathbf{x}^j, \{p^{jm}\}_{m \in M_j})\}_j$, and young consumer choices and beliefs $\hat{V}(\mathbf{x}, p)$ such that:

1. Each firm j chooses r^j, $\mathbf{x}^j$, and $\{p^{jm}\}_{m \in M_j}$ to maximize profits (Equation 3)
2. Each consumer i chooses $(\mathbf{x}, p) \in \{(\mathbf{x}^j, \{p^{jm}\}_{m \in M_j})\}_j$ to maximize anticipated utility (Equation 2)
3. Markets clear: Q^{jm} equals the fraction of consumers purchasing choice jm

This equilibrium is partial in that does not enforce consistency on consumer beliefs. Consumers are likely to have difficulty forming correct beliefs in this setting.

A **full equilibrium** adds a consistency condition:

4. Consumer beliefs $\hat{V}(\mathbf{x}, p) = E[V(\mathbf{z})|\mathbf{x}, p]$ are consistent with firm production choices

4.4 Sequence

In the *first period* (representing a historical period), firms have access only to a historical production process $r = 0$ with fixed quality $\mathbf{z}_0 \overset{iid}{\sim} F$. Because the production process is fixed, it is natural for consumers to believe that all goods are identical: $\hat{V}(\mathbf{x}, p) \equiv \hat{V}_0$, so that $\mathbf{x}$ is irrelevant. In either partial or full equilibrium, all firms with market share produce the lowest cost observable $\underline{\mathbf{x}}$ and charge marginal cost: $p_0 = c(\mathbf{z}_0, \underline{\mathbf{x}})$. Consider the case that $\hat{V}_0 \geq \beta p_0$ so that the good is produced and consumed by the first generation.

[20] The placement fee allows firms with low production costs to edge out firms with higher costs, without signaling to consumers.

In the *second period* (representing the present), the first generation receives actual utility $V(\mathbf{z}_0)$, and the second generation selects goods. Firms now have access to both the historic production process ($r = 0$), and a new process ($r = 1$) made possible through innovation. The new process has a different draw of quality $\mathbf{z}_1 \overset{iid}{\sim} F$ and marginal cost $c(\mathbf{z}_1, \mathbf{x})$. Innovations may be welfare improving or reducing.

In the *third period* (representing a period to come in the future), the second generation receives actual utility $V(\mathbf{z})$.

I focus on behavior in the second period.

4.5 Effects of innovation

I consider two stark cases: where $\mathbf{z}_r$ is observed, and where it is prohibitively costly to communicate. Let $\Delta V = V(\mathbf{z}_1) - V(\mathbf{z}_0)$.

Implication 1: When quality is observable ($\mathbf{x} = \mathbf{z}$), innovation weakly improves expected welfare. When quality is hidden ($\mathbf{x} = \emptyset$), innovation has ambiguous effects on expected welfare.

When quality is observable to consumers, $\mathbf{x} = \mathbf{z}$. Let $\Delta c = c(\mathbf{z}_1, \mathbf{z}_1) - c(\mathbf{z}_0, \mathbf{z}_0)$. The innovative good will be sold only if it improves utility net of cost. Only the highest net value good will be exchanged on the market, at price $p_r = c(\mathbf{z}_r, \mathbf{z}_r)$.[21] Innovation weakly improves welfare by:

$$E\left[\frac{1}{\beta}\Delta V - \Delta c \left| \frac{1}{\beta}\Delta V - \Delta c \geq 0 \right.\right]$$

When $\mathbf{z}$ is hidden and consumers observe no more information, $\mathbf{x} = \emptyset$. For convenience I drop $\mathbf{x}$ from subscripts and arguments. Let $\Delta c = c(\mathbf{z}_1) - c(\mathbf{z}_0)$. The innovation will be used if it reduces cost, regardless of its effect on welfare. Only the lowest cost goods will be exchanged on the market, at prices equal to cost.[22] If the historic process continues to be lowest cost, the second period repeats the first. The effect of innovation on welfare is ambiguous:

$$\frac{1}{\beta}E\left[\Delta V \,|\Delta c \leq 0\right] - E\left[\Delta c \,|\Delta c \leq 0\right]$$

The second term (cost reductions) increases welfare. However, the first term (hidden effects on utility) can be negative if quality is costly to produce (both V and c are monotonic in $\mathbf{z}$), so that cost reductions are accompanied by declines in hidden quality.

[21] If a noninnovative firm has market share, it must charge $p_0 = c_0$; if an innovative firm has market share it must charge $p_1 = c_1$.

[22] Because in partial equilibrium, lower cost products are offered at both low and high prices, price does not signal quality, and beliefs are flat in price.

When consumers are sufficiently low income (high β), innovation improves welfare. But as consumers become wealthier, if the first term is negative the net effect of innovation decreases and can become negative. Innovation can also lower welfare if second generation consumers observe the utility provided to the previous generation. For example, if they observe that $V(\mathbf{z}_0) > \kappa$ for some subsistence level κ, this bounds the downside of the historical process, but leaves the downside of the innovative process unknown.

These results can explain why consumers have become pessimistic about innovation in food as incomes have risen (β decreases). Food has seen dramatic process innovation, but has many dimensions of quality (high K) that are prohibitively costly to communicate in market exchange. In contrast, other outputs from agricultural production processes (textiles, wool, leather and down) have fewer effective dimensions of quality.

This paper focuses on the implication that the economy may overuse cost-reducing innovations. But the economy will also underuse innovations that improve hidden quality if they also increase cost, suggesting that these markets may have untapped welfare-improving innovations.

Illuminating hidden tradeoffs

I test for changes in hidden dimensions of quality in Appendix C using experimental evidence on historical wheat breeding in the U.S. I compile the results of randomized controlled field trials and find that the past century of wheat breeding has improved observables but deteriorated mineral content, a dimension that was hidden. There is also suggestive evidence that innovation has altered dimensions of quality in other agricultural products.

Next I consider the ability of firms to signal hidden quality.

4.6 Signaling through attributes

Consider the case where quality is hidden and consumers observe an attribute $\mathbf{x} = a \in \{A, B, C, ...\}$. These values may represent labels (e.g., artisanal, local), intrinsic properties of the good (e.g., color or shape), or disclosed information (e.g., ingredients, nutrition facts). I make the stark assumption that this attribute provides no intrinsic value, and show that under some conditions consumers will still demand it as a signal.

I focus on the case where innovation lowers costs and so is implemented.

Without loss of generality, let the observables be ordered by marginal cost under the historical process, so that $c(\mathbf{z}_0, A) < c(\mathbf{z}_0, B) < c(\mathbf{z}_0, C) \cdots$. In the first period only the lowest cost observable $\mathbf{x} = A$ will be produced. Assume that the innovation lowers the cost of producing A: $c(\mathbf{z}_1, A) < c(\mathbf{z}_0, A)$.

Due to the hiddenness of $\mathbf{z}$, the game is unlikely to equilibrate immediately. I step through the process of equilibration and consider the outcomes at different stages in the process. Under either a partial equilibrium where consumers believe that the good has not changed ($\hat{V}(\mathbf{x}, p) = \hat{V}_0$), or a full equilibrium, any goods with attribute A that are exchanged over the market will be sold at the lowest cost, $p_{1,A} = c(\mathbf{z}_1, A)$. Full equilibrium beliefs consistent with this are $\hat{V}(A, p) = V(\mathbf{z}_1)$, which are flat in price.

Observables can lead to a separating equilibrium if observable B is more costly to produce with the innovative production technology: $c(\mathbf{z}_1, B) \geq c(\mathbf{z}_0, B)$. The historical good will then be offered at price $p_{0,B} = c(\mathbf{z}_0, B)$. In a full equilibrium it is consistent for consumers to believe that B is associated with the historical process: $\hat{V}(B, p) = V(\mathbf{z}_0)$.

Implication 2: If innovation lowers costs and consumers believe it lowers welfare, they may demand costly signals of hidden quality. To be stable, signaling attributes must be differentially costly to produce under the innovative technology. If $\hat{V}(B, p) - \hat{V}(A, p) \geq \beta\,(p_{0,B} - p_{1,A})$, then consumers will demand the inefficient production choice B as a costly signal of quality level $\mathbf{z}_0$.

This is consistent with consumers demanding nostalgic production, rather than directly demanding individual underlying attributes, which may be easy to mimic. For example, consumers may demand heirloom varieties of crops like tomatoes, which have skipped recent beneficial innovations but are visually distinct (wrinkly) and difficult to produce with modern processes. This can explain why consumers demand nostalgic processes, rather than futuristic or alternative contemporaneous processes: only the former will be differentially costly under innovative technologies. It also explains why this preference extends to the outputs of these processes rather than the processes themselves. Consumers demand nostalgic food crops, milk, and eggs, but not biofuels, leather, or down, which are nonfood outputs of nearly identical agricultural processes but have fewer hidden dimensions of quality.

Comparative Statics

Implication 3: Demand for signaling attributes increases in income ($\frac{1}{\beta}$).

Implication 4: Demand for signaling attributes decreases if hidden quality is made visible. If either hidden attributes $\mathbf{z}$ or the production decision r is made observable, then consumers will purchase goods without regard to the signaling attribute a. This is consistent with the results of the choice experiment.

Rationality

Implication 5: Demand for signaling attributes depends on consumer beliefs $\hat{V}$. Consumers with different beliefs may demand different signaling attributes. In particular, if innovation lowers welfare but consumers do not update their beliefs, they will underdemand signals. Alternately, consumers with overly pessimistic beliefs will overdemand signals.

Surveys suggest that Americans have different beliefs about nostalgic labels: 49% of adults believe that genetically modified foods are worse for health, and 45% believe that organic fruits and vegetables are better for health than conventionally grown foods (Pew Research Center, 2018). 51% believe that the average person is exposed to additives in food that they eat every day which pose a serious risk to health, while 48% believe they are in such small amounts that the health risk is not serious.

Differences in demand for nostalgic production between professions could result from different valuation of quality ($\frac{1}{\beta}$) or different beliefs $\hat{V}$. Beliefs about signals, or the value of quality can differ between goods with different production processes, consistent with differences between demand for local milk and eggs.

Implication 6: Consumer behavior can appear irrational to observers who do not consider hidden quality. An observer who was unaware of hidden quality (who believed that $\hat{V}(\mathbf{x}, p) \equiv g(\mathbf{x})$ for some fixed function g) would see first generation consumers choose $\mathbf{x} = A$, suggesting $g(\mathrm{A}) - g(\mathbf{x}) \geq \beta\,(p_{0,A} - p_{0,\mathbf{x}})$ for all $\mathbf{x}$. In the second period, the observer would see that a reduction in the price of A induces second generation consumers to switch to B, thereby suggesting $g(\mathrm{A}) - g(B) \leq \beta\,(p_{1,A} - p_{0,B}) < \beta\,(p_{0,A} - p_{0,B})$, a failure of the weak axiom of revealed preference. If the observer also knows that the price change arose from a new production technology, consumers will appear to be biased against new technology with false nostalgia: the introduction of a new technology drives demand for a production choice that was previously revealed to be inefficient.

This implication is consistent with observers who claim that preferences for attributes like local production or heirloom varieties are irrational (Desrochers and Shimizu, 2012).

4.7 Unstable signaling

However, signaling equilibria need not be stable. Consider the case where observable B is less costly to produce with the innovative production technology: $c(\mathbf{z}_1, B) < c(\mathbf{z}_0, B)$.

Implication 7: 'Fads': A stable signaling equilibrium may not exist. Consider a natural process of equilibration, where consumers initially believe that the good has not changed, $\hat{V}(\mathbf{x}, p) \equiv \hat{V}_0$. Innovative firms undercut the prices for A. Consumers update beliefs correspondingly, $\hat{V}(A, p) \equiv V(\mathbf{z}_1)$ but still believe B offers $\hat{V}(B, p) \equiv \hat{V}_0$, so demand B as a signal of quality. Innovative firms undercut prices for B. Consumers then update beliefs for B, $\hat{V}(B, p) \equiv V(\mathbf{z}_1)$, but believes C still offers $\hat{V}(C, p) \equiv \hat{V}_0$. If the innovative process can more cheaply produce every observable ($c(\mathbf{z}_1, \mathbf{x}) < c(\mathbf{z}_0, \mathbf{x})$), then this may not reach an equilibrium: consumers will demand fringe attributes until they become mainstream. If consumers have heterogeneous price sensitivities (β) or beliefs, then demand can be split among different attributes.

4.8 Policy

Policy Implication A: Lowering the cost of demanded attributes can undermine demand. Consider the stable signaling case ($c(\mathbf{z}_1, B) \geq c(\mathbf{z}_0, B)$), where innovation induces demand to switch from observable A to B. Attempting to meet demand for B by lowering $c(\mathbf{z}_1, B)$ can undermine the signaling value of B and tip the equilibrium into the unstable case. Consumers never valued B per se; what they do value is lost if supply is naïvely scaled up. As a result, demand for B may collapse and consumers may seek out a costlier, more eccentric signaling attribute. Straightforward policies to increase supply can lower welfare.

This implication is consistent with the differential effects of expertise on local purchases in highly local markets. In egg producing markets, it is low cost to produce local eggs. Experts are less likely to purchase local eggs in these markets.

These processes may explain a shift in consumer preferences from organic to local food. Initially, organic certification differed from state to state, which limited the scale of production. After the implementation of the national organic standard in 2002, the size of organic farms increased, allowing organic products to be produced at lower cost for larger markets. However, some argued that this undermined what consumers wanted: "This isn't what we meant. When we said organic, we meant local. We meant healthful. We meant being true to the ecologies of our regions..." (Gussow, 2002). Organic certification appears to have coincided with a rise in demand for local production. A metaanalysis suggests that finds weak and in some cases negative willingness to pay for local production in the 1980s, reversing to valuing local production more than organic in the years following implementation of the national standard (Adams and Salois, 2010). Coinciding with the emergence of other nostalgic labels, the percent of U.S. adults who say organic fruits and vegetables are generally better one's health than conventionally grown produce declined by 10 percentage points from 2016 to 2018 (Pew Research Center, 2018).

In response to increased demand for local food, policymakers are working to increase the scale of local production (Martinez, 2016). If consumers demand local production solely as a signal, increasing the scale of its production could undermine its signaling value and may result in demand eventually shifting to other attributes.

Policy Implication B: When quality is hidden, there may be untapped quality improving innovations. The model suggests these markets will tend to overimplement cost reducing innovations, even when they lower hidden quality. It also suggests these markets will underimplement innovations that increase hidden quality when they increase production costs. If it is possible to better measure or communicate quality, it may be possible to tap these potential innovations.

5 Conclusion

This paper develops evidence on, and an explanation for, rising demand for local and nostalgic production in modern food markets. If goods are more complex than can be represented in market exchange, innovations that make production functions more flexible can have ambiguous effects on welfare. As incomes rise, consumers who believe that quality has declined may seek out nostalgic modes of production.

Flexible production functions can make it easier to mimic desired signals; as a result, products can become more difficult to distinguish. Policies to increase the scale of nostalgic production can undermine its signaling value and may result in demand shifting to increasingly distant proxies of quality.

If consumers dislike side effects of innovation, rather than innovation per se, it may be possible to satisfy consumer demand without being constrained to historical vintages of technology. But it also raises several deep questions. How do markets function when goods have more dimensions of quality than can be measured and communicated? How should societies navigate innovations that expose hidden tradeoffs?

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Appendix

A Consumer Choice Data

I define three occupational categories*:*

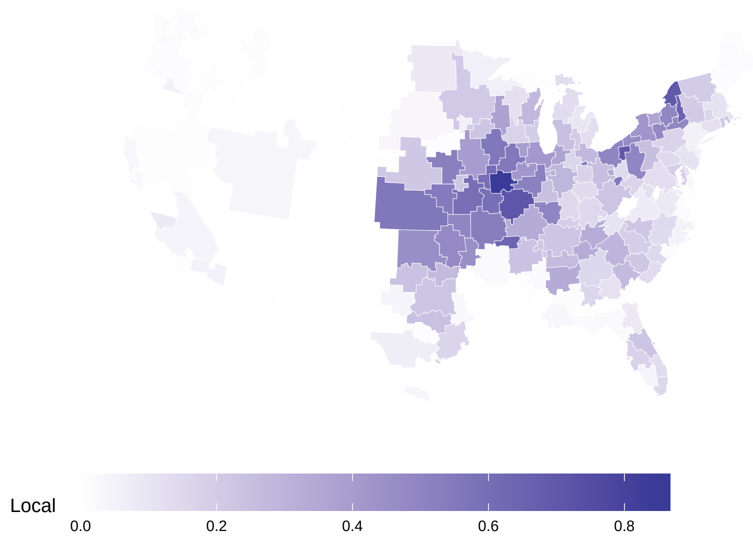
Health professions include physicians and surgeons; registered nurses; and dietitians and nutritionists.

Food production includes butchers and other meat, poultry, and fish processing workers; agricultural and food scientists; agricultural inspectors; farmers and ranchers; graders and sorters, agricultural products; miscellaneous agricultural workers; farm, ranch, and other agricultural managers; purchasing agents and buyers, farm products; first-line supervisors/managers of farming, fishing, and forestry workers; food and tobacco roasting, baking, and drying machine operators and tenders; food batchmakers; food cooking machine operators and tenders; and other food production.

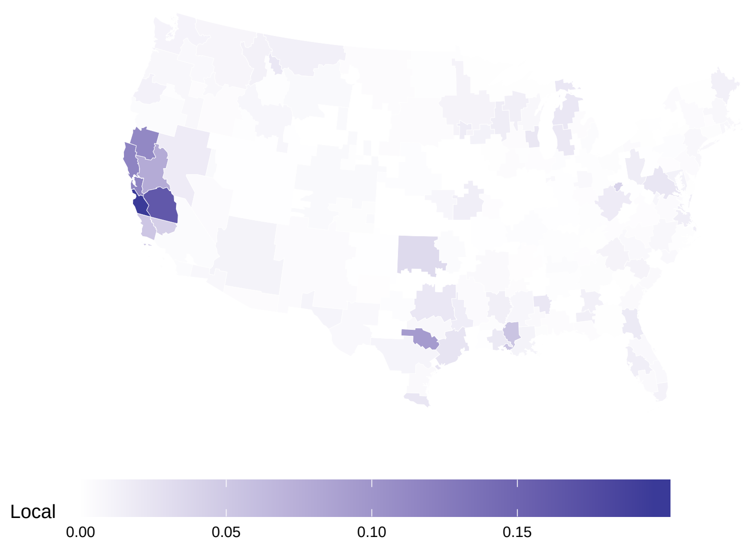
Food preparation and serving includes chefs and head cooks; bakers; cooks; food service managers; first-line supervisors/managers of food preparation and serving workers; food preparation workers; combined food preparation and serving workers, including fast food; food preparation and serving related workers, all other; and other food preparation.

Figure A1: Local Purchases

(a) Eggs



(b) Milk



Proportion of eggs and milk volume (fluid ounces) that have local label purchased by Nielsen Homescan panelists in 2016, by DMA. Includes purchases of UPCs in Label Insight database.

Table A1: Milk Purchases: Individual Labels 2016

	Organic		Local		Family Farm		Non GMO		Pasture Raised		Grass Fed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CollegeEducated	0.021***	0.006**	−0.0004	0.001	0.002	−0.005	0.022***	0.012***	0.005***	0.003**	0.0003	−0.001
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)	(0.0003)	(0.001)
Income[40-60)	0.006***	0.009**	0.002**	−0.003	−0.001	−0.009**	0.005**	−0.003	0.002**	−0.0004	0.0005	−0.0001
	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.002)	(0.0004)	(0.001)
Income[60-100)	0.018***	0.015***	0.003***	−0.002	0.004*	−0.003	0.017***	0.008*	0.003***	0.002	0.001**	0.001
	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.002)	(0.0004)	(0.001)
Income[100,)	0.044***	0.038***	0.008***	0.0004	0.017***	0.016***	0.044***	0.025***	0.008***	0.006***	0.003***	0.003***
	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.002)	(0.0004)	(0.001)
OFood Prep/Serving		0.006		−0.008		−0.024*		0.0004		−0.003		0.0002
		(0.011)		(0.006)		(0.012)		(0.012)		(0.005)		(0.003)
OFood Production		−0.004		−0.006		−0.002		0.043		−0.004		−0.001
		(0.025)		(0.014)		(0.029)		(0.029)		(0.012)		(0.007)
OHealth Profession		0.021		0.016*		0.026		−0.001		−0.0005		0.002
		(0.018)		(0.010)		(0.020)		(0.020)		(0.008)		(0.005)
Market fixed effects?	X	X	X	X	X	X	X	X	X	X	X	X
Demographic controls?	X	X	X	X	X	X	X	X	X	X	X	X
Mean of dep. variable	0.037	0.027	0.012	0.010	0.037	0.040	0.039	0.030	0.007	0.007	0.002	0.002
Sample	All	Surveyed	All	Surveyed	All	Surveyed	All	Surveyed	All	Surveyed	All	Surveyed
	All UPCs	All UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs
N	57,849	15,019	51,414	13,185	51,414	13,185	51,414	13,185	51,414	13,185	51,414	13,185
R^2	0.053	0.059	0.067	0.086	0.081	0.129	0.050	0.067	0.018	0.061	0.007	0.022
Adjusted R^2	0.049	0.045	0.063	0.071	0.077	0.114	0.046	0.051	0.014	0.045	0.003	0.006

Notes:

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
Dependent variable is fraction of total milk volume purchases with given attribute. Standard errors in parentheses.
Household income reported in thousands of dollars; omitted category is household incomes below $40,000.
Demographic controls include household composition, presence of children, and household head's race, gender, and age.

Table A2: Egg Purchases: Individual Labels 2016

	Organic		Cage Free		Local		Family Farm		Non GMO		Pasture Raised		Free Range	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
CollegeEducated	0.017***	0.011***	0.030***	0.014***	0.004	−0.004	0.004***	0.004*	0.013***	0.004	0.002***	0.001	0.007***	0.001
	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)	(0.006)	(0.001)	(0.002)	(0.001)	(0.003)	(0.0005)	(0.001)	(0.001)	(0.002)
Income[40-60)	0.006***	0.0001	0.009***	−0.001	−0.005	0.003	−0.0004	−0.004	0.002	−0.005	−0.001	−0.003***	−0.001	0.0002
	(0.002)	(0.004)	(0.002)	(0.005)	(0.004)	(0.008)	(0.001)	(0.003)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)
Income[60-100)	0.014***	0.011***	0.026***	0.020***	−0.034***	−0.032***	0.003***	0.002	0.010***	−0.001	0.001	−0.001	0.003**	0.002
	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)	(0.008)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)
Income[100,)	0.037***	0.033***	0.057***	0.046***	−0.058***	−0.059***	0.010***	0.011***	0.021***	0.015***	0.002***	−0.0001	0.012***	0.015***
	(0.002)	(0.004)	(0.003)	(0.005)	(0.004)	(0.008)	(0.001)	(0.003)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)
OFood Prep/Serving		−0.017		−0.028*		−0.018		0.048***		0.030***		0.002		0.043***
		(0.012)		(0.015)		(0.025)		(0.008)		(0.011)		(0.003)		(0.009)
OFood Production		0.007		0.015		0.206***		−0.005		0.001		−0.0004		−0.002
		(0.022)		(0.028)		(0.049)		(0.016)		(0.022)		(0.006)		(0.017)
OHealth Profession		−0.021		0.015		−0.031		−0.003		−0.008		−0.004		−0.014
		(0.015)		(0.019)		(0.033)		(0.010)		(0.015)		(0.004)		(0.011)
Market fixed effects?	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Demographic controls?	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Mean of dep. variable	0.046	0.037	0.069	0.058	0.153	0.170	0.015	0.014	0.031	0.025	0.004	0.003	0.019	0.017
Sample	All	Surveyed	All	Surveyed	All	Surveyed	All	Surveyed	All	Surveyed	All	Surveyed	All	Surveyed
	All UPCs	All UPCs	All UPCs	All UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs	LI UPCs
N	58,706	15,283	58,706	15,283	48,316	12,394	48,316	12,394	48,316	12,394	48,316	12,394	48,316	12,394
R^2	0.051	0.069	0.062	0.076	0.216	0.256	0.042	0.085	0.038	0.058	0.021	0.054	0.047	0.080
Adjusted R^2	0.048	0.056	0.059	0.062	0.212	0.243	0.037	0.068	0.034	0.041	0.016	0.037	0.043	0.064

Notes:

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
Dependent variable is fraction of total egg purchases with given attribute. Standard errors in parentheses.
Household income reported in thousands of dollars; omitted category is household incomes below $40,000.
Demographic controls include household composition, presence of children, and household head's race, gender, and age.

Table A3: Comparison between Nielsen and Label Insight Samples: Milk Purchases 2016

	Organic					Organic (LI)
	(1)	(2)	(3)	(4)	(5)	(6)
CollegeEducated	0.023***	0.021***	0.006**	0.024***	0.022***	0.012***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Income[40-60)	0.006***	0.006***	0.009**	0.006**	0.005**	−0.003
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)
Income[60-100)	0.019***	0.018***	0.015***	0.018***	0.017***	0.008*
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)
Income[100,)	0.048***	0.044***	0.038***	0.047***	0.044***	0.025***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)
OFood Prep/Serving			0.006			0.0004
			(0.011)			(0.012)
OFood Production			−0.004			0.043
			(0.025)			(0.029)
OHealth Profession			0.021			−0.008
			(0.018)			(0.020)
Market fixed effects?		X	X		X	X
Demographic controls?	X	X	X	X	X	X
Mean of dep. variable	0.037	0.037	0.027	0.039	0.039	0.030
Sample	All All UPCs	All All UPCs	Surveyed All UPCs	All LI UPCs	All LI UPCs	Surveyed LI UPCs
N	57,849	57,849	15,019	51,414	51,414	13,185
R^2	0.036	0.053	0.059	0.033	0.050	0.067
Adjusted R^2	0.036	0.049	0.045	0.033	0.046	0.051

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
Dependent variable is fraction of total milk volume purchases with given attribute. Standard errors in parentheses.
Household income reported in thousands of dollars; omitted category is household incomes below $40,000.
Demographic controls include household composition, presence of children, and household head's race, gender, and age.

Table A4: Comparison between Nielsen and Label Insight Samples: Egg Purchases 2016

	Organic			Organic (LI)			Cage Free			Cage Free (LI)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CollegeEducated	0.018***	0.017***	0.011***	0.011***	0.010***	−0.002	0.031***	0.030***	0.014***	0.019***	0.018***	0.005
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Income[40-60)	0.006***	0.006***	0.0001	−0.003	0.001	−0.004	0.009***	0.009***	−0.001	0.008***	0.007***	−0.005
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.005)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.005)
Income[60-100)	0.016***	0.014***	0.011***	0.002	0.006**	−0.014***	0.027***	0.026***	0.020***	0.027***	0.026***	0.012***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)
Income[100,)	0.041***	0.037***	0.033***	0.008***	0.015***	0.009*	0.061***	0.057***	0.046***	0.042***	0.040***	0.021***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.005)	(0.002)	(0.003)	(0.005)	(0.002)	(0.003)	(0.005)
OFood Prep/Serving			−0.017			0.070***			−0.028*			−0.027*
			(0.012)			(0.015)			(0.015)			(0.014)
OFood Production			0.007			−0.042			0.015			0.005
			(0.022)			(0.030)			(0.028)			(0.028)
OHealth Profession			−0.021			−0.024			0.015			0.032*
			(0.015)			(0.020)			(0.019)			(0.019)
Market fixed effects?		X	X		X	X		X	X		X	X
Demographic controls?	X	X	X	X	X	X	X	X	X	X	X	X
Mean of dep. variable	0.046	0.046	0.037	0.064	0.064	0.055	0.069	0.069	0.058	0.056	0.056	0.045
Sample	All	All	Surveyed	All	All	Surveyed	All	All	Surveyed	All	All	Surveyed
	All UPCs	All UPCs	All UPCs	LI UPCs	LI UPCs	LI UPCs	All UPCs	All UPCs	All UPCs	LI UPCs	LI UPCs	LI UPCs
N	58,706	58,706	15,283	48,316	48,316	12,394	58,706	58,706	15,283	48,316	48,316	12,394
R^2	0.030	0.051	0.069	0.010	0.070	0.125	0.041	0.062	0.076	0.028	0.068	0.095
Adjusted R^2	0.030	0.048	0.056	0.010	0.066	0.109	0.041	0.059	0.062	0.027	0.064	0.079

Notes:
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
Dependent variable is fraction of total egg purchases with given attribute. Standard errors in parentheses.
Household income reported in thousands of dollars; omitted category is household incomes below $40,000.
Demographic controls include household composition, presence of children, and household head's race, gender, and age.

Table A5: Differential for Farmers: Milk Purchases 2016

	Nostalgic Label					Local		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CollegeEducated	0.019***	0.017***	0.020***	0.005	0.0001	−0.0004	−0.0002	0.001
	(0.002)	(0.002)	(0.002)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)
Income[40-60)	0.002	0.002	−0.002	−0.011**	0.002**	0.002**	0.003**	−0.003
	(0.003)	(0.003)	(0.003)	(0.006)	(0.001)	(0.001)	(0.001)	(0.002)
Income[60-100)	0.017***	0.016***	0.013***	0.002	0.003***	0.003***	0.004***	−0.002
	(0.003)	(0.003)	(0.003)	(0.005)	(0.001)	(0.001)	(0.001)	(0.002)
Income[100,)	0.054***	0.051***	0.047***	0.036***	0.010***	0.008***	0.009***	0.0004
	(0.003)	(0.003)	(0.003)	(0.006)	(0.001)	(0.001)	(0.001)	(0.002)
Farmer			−0.019*				0.005	
			(0.011)				(0.004)	
OFood Prep/Serving				−0.029*				−0.008
				(0.016)				(0.006)
OFood Production				0.047				−0.006
				(0.038)				(0.014)
OHealth Profession				0.0004				0.016*
				(0.027)				(0.010)
Market fixed effects?		X	X	X		X	X	X
Demographic controls?	X	X	X	X	X	X	X	X
Mean of dep. variable	0.065	0.065	0.065	0.062	0.012	0.012	0.012	0.010
Sample	All LI UPCs	All LI UPCs	All LI UPCs	Surveyed LI UPCs	All LI UPCs	All LI UPCs	All LI UPCs	Surveyed LI UPCs
N	51,414	51,414	47,033	13,185	51,414	51,414	47,033	13,185
R^2	0.023	0.065	0.065	0.101	0.006	0.067	0.065	0.086
Adjusted R^2	0.023	0.061	0.061	0.085	0.006	0.063	0.061	0.071

Notes:

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
Dependent variable is fraction of total milk volume purchases with given attribute. Standard errors in parentheses.
Household income reported in thousands of dollars; omitted category is household incomes below $40,000.
Demographic controls include household composition, presence of children, and household head's race, gender, and age.

Table A6: Differential for Farmers: Egg Purchases 2016

	Nostalgic Label				Local					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CollegeEducated	0.035***	0.032***	0.032***	0.013***	0.005	0.004	0.006**	−0.004	0.010***	−0.007
	(0.002)	(0.002)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)	(0.006)
Income[40-60)	0.010***	0.008**	0.009***	−0.008	0.001	−0.005	−0.009**	0.003	−0.0004	−0.010
	(0.003)	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)	(0.009)
Income[60-100)	0.033***	0.031***	0.035***	0.010*	−0.032***	−0.034***	−0.038***	−0.032***	−0.029***	−0.023***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)	(0.008)
Income[100,)	0.065***	0.061***	0.062***	0.044***	−0.063***	−0.058***	−0.064***	−0.059***	−0.054***	−0.064***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)	(0.009)
Egg producing region:CollegeEducated									−0.033***	0.018
									(0.009)	(0.018)
Egg producing region:Income[40-60)									−0.076***	0.090***
									(0.012)	(0.023)
Egg producing region:Income[60-100)									−0.077***	−0.058***
									(0.012)	(0.022)
Egg producing region:Income[100,)									−0.093***	0.048**
									(0.012)	(0.023)
Egg producing region:Farmer									−0.014	
									(0.049)	
Farmer			0.008				−0.001		0.003	
			(0.015)				(0.018)		(0.019)	
Egg producing region:OFood Prep/Serving										−0.027
										(0.068)
Egg producing region:OFood Production										−0.640***
										(0.148)
Egg producing region:OHealth Profession										−0.253**
										(0.102)
OFood Prep/Serving				−0.0001				−0.018		−0.017
				(0.020)				(0.025)		(0.028)
OFood Production				0.016				0.206***		0.298***
				(0.038)				(0.049)		(0.053)
OHealth Profession				0.028				−0.031		0.001
				(0.026)				(0.033)		(0.035)
Market fixed effects?		X	X	X		X	X	X	X	X
Demographic controls?	X	X	X	X	X	X	X	X	X	X
Mean of dep. variable	0.092	0.092	0.089	0.081	0.153	0.153	0.154	0.170	0.154	0.170
Sample	All LI UPCs	All LI UPCs	All LI UPCs	Surveyed LI UPCs	All LI UPCs	All LI UPCs	All LI UPCs	Surveyed LI UPCs	All LI UPCs	Surveyed LI UPCs
N	48,316	48,316	44,322	12,394	48,316	48,316	44,322	12,394	44,322	12,394
R^2	0.036	0.075	0.076	0.096	0.013	0.216	0.218	0.256	0.220	0.261
Adjusted R^2	0.035	0.071	0.071	0.080	0.013	0.212	0.214	0.243	0.216	0.247

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
Dependent variable is fraction of total egg purchases with given attribute. Standard errors in parentheses.
Household income reported in thousands of dollars; omitted category is household incomes below $40,000.
Demographic controls include household composition, presence of children, and household head's race, gender, and age.

B Choice Experiment

Design

To gauge the signaling value of origin, I conducted a choice experiment on Amazon Mechanical Turk (for more information about running experiments on this platform, see Paolacci et al. (2010) and Horton et al. (2011)). Participants were required to be in the U.S., to have approval ratings of at least 95%, and to have completed at least 100 tasks on the platform. 132 respondents from 39 different states participated, who were recruited the week of February 20th, 2017. The top panel of Table A8 reports participant demographics.

To avoid selection into the survey based on food preferences, the task was advertised generically under the title, 'Choice Survey (∼20 minutes)', with the description, 'This is a survey about choices between products.' The task was advertised as paying $3, and was required to be completed within 2 hours of starting.[23]

An initial screen provided the following instructions:

> 'In this study we will ask you to choose between a series of different products, as if you were shopping for groceries. You'll make a series of 45 choices, and then respond to a short survey.
>
> For each choice, you will be presented with the attributes of two different products and asked to select between them. Please select the product you would purchase in real life, if you were in the market for tomatoes.
>
> Your payment: for completing this study, you will receive a minimum payment of $3 within 24 hours. Additionally, you can receive a bonus of up to $0.40:
>
> Bonus: Within the study, 4 choices will be repeated. In these choices, the products may switch places, and their attributes may be listed in a different order. For each choice where you select the same product as your previous answer, you will receive a bonus payment of $0.10.[24] The bonus will be paid within one week.
>
> To receive the bonus, consider each choice carefully, and consistently select the product you would select in real life.'

After successfully completing a check for understanding of these instructions, participants began the choice tasks. Each choice task involved a selection between two identical looking tomatoes with different attributes, or the option of purchasing neither. Attributes were drawn uniformly at random from the list in Table A7. The selection of attributes that are associated with local production and these particular attribute levels were informed by

[23] For 9 initial participants the task paid $2.
[24] For 9 initial participants the bonus was $0.25.

Table A7: Choice Experiment Attribute Space

Attribute	Used in Part	Possible Values
Price	1, 2a, 2b	$1.49/lb, $1.89/lb, $2.29/lb, $2.69/lb, $3.09/lb, or $3.49/lb
Origin	1, 2a, 2b	Locally grown, Grown in a different state
Freshness	2a	Harvested yesterday, Harvested 2 weeks ago
Organic	2a	Organic, Conventional
Flavor	2b	Sweet flavor, Tart flavor
Size	2b	Cherry size, Standard size

previous analyses of the value of local food, primarily Onozaka and Mcfadden (2011), but also Darby et al. (2008).

The choice tasks were given in two parts. Participants were randomly assigned to answer these parts in different orders (part 1 then 2, or part 2 then 1). In part 1, participants chose between tomatoes based on price and whether the tomato was grown locally or in a different state. Each participant completed 5 tasks, drawn randomly from the 36 potential combinations of attributes.

In part 2, participants were shown more attributes. Consumers were randomly assigned to either part 2a or 2b. Part 2a showed price, origin, and vertical quality attributes: harvest date, and organic status. Part 2b showed price, origin, and horizontal quality attributes: flavor (sweet or tart) and size (cherry or standard). Each participant completed 36 tasks, drawn randomly from the 1,008 potential combinations of attributes, and then repeated a random subset of 4 of the 36 tasks.

Screens from the survey are shown in Figure A2. The position of the two items in the task was randomized, so that each bundle of attributes was equally likely to be shown on the left or on the right. The order of attributes was randomized across participants, but was held fixed within a participant to help them make comparisons. The 4 repeated items were shown in random positions that may have differed from the original presentation, and in an order that differed from the original for 2/3 of subjects.

After the 45 comparison tasks, participants were asked follow up questions about their performance in the tasks and demographics.

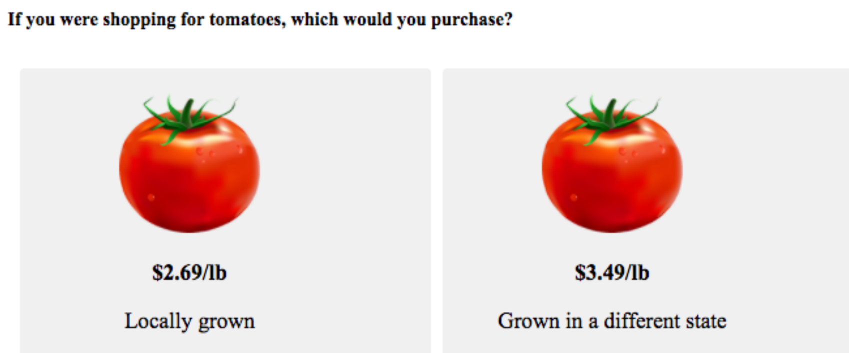
The design included several checks to ensure that respondents took the survey seriously. First, after reading the instructions, participants responded to two simple multiple choice questions to validate understanding of the study. In order to complete the study, participants had to respond correctly. Second, each choice could only be submitted after a delay (3 seconds on part 1 and 5 second on part 2), so that respondents were guaranteed time to think about each decision. Third, as described in the experiment directions, a random subset of 4 choice tasks were repeated. Participants received a bonus if they answered these tasks consistently with their previous answers, which provided an incentive for participants to carefully consider each choice. These repeated choices also provide a measure of internal consistency. Finally, in the final demographic survey, respondents were asked to rate the following three statements along the same Likert scale ranging from 'Strongly Disagree' to 'Strongly Agree': 'I made each decision in this study carefully', 'I made decisions in this study randomly', and 'I understood what my decisions meant.' A careful respondent should agree with the first and last statement but disagree with the middle; agreement or disagreement with all statements reveals that a respondent made careless decisions. The bottom panel of Table A8 reports these measures of consistency, finding substantial evidence that respondents took the survey seriously.

Another potential concern is that the order of the parts may have an effect on participant responses. In particular, respondents that see part 1 first may focus on origin when reaching part 2; or participants that see part 2 first may infer the correlation between origin and other attributes from the distribution of choices they faced, and use this information when responding to part 1. To test for ordering effects, Table A9 shows the main experiment effects as well as the estimates when the sample is restricted to respondents who observed each part first (so their responses are uncontaminated). Results are consistent with the main experimental results.

Another potential concern is that consumers may focus on the most important attributes, which could lead them to pay differential attention to origin between parts 2a and 2b. However, the implied valuations for the horizontal attributes are higher than the vertical attributes, suggesting any such bias would be in the opposite direction.

Figure A2: Experimental Screens

(a) Part 1: Preferences for Origin (Unconditional)



(b) Part 2a: Preferences for Origin (Conditional)

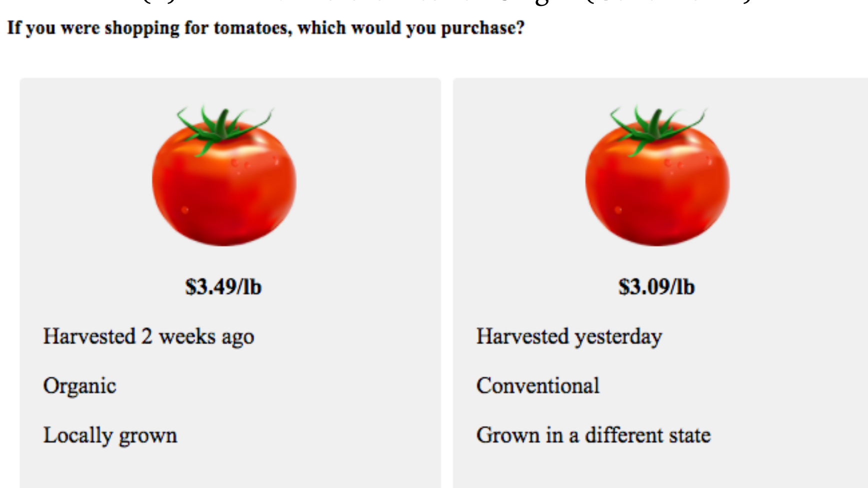


Table A8: Experiment Demographics

Variable	Response	Mean
Age		33.20
Male		0.55
HHSize		2.58
PrimaryShopper		0.82
FractionOfHouseholdGroceries		0.78
Education	High School or equivalent	0.18
	Some college	0.26
	College Graduate with Associate's Degree (2 year)	0.20
	College Graduate with Bachelor's Degree (4 year)	0.32
	Master's Degree (MS)	0.03
	Professional Degree (MD, JD, etc.)	0.02
Race	Asian	0.07
	Black or African American	0.05
	Hispanic	0.06
	White, non Hispanic	0.80
	Other	0.02
HHIncome	Less than $10,000	0.08
	$10,000 - $19,999	0.08
	$20,000 - $29,999	0.16
	$30,000 - $39,999	0.17
	$40,000 - $49,999	0.09
	$50,000 - $59,999	0.09
	$60,000 - $69,999	0.08
	$70,000 - $79,999	0.08
	$80,000 - $89,999	0.08
	$90,000 - $99,999	0.05
	$100,000 - $149,999	0.05
	More than $150,000	0.01
MTurkImportance	I do it just for fun / because I have nothing better to do	0.02
	It's not vital, but a welcome addition to my finances	0.43
	It's not my main source of income, but I do need it to get by	0.30
	It's my main source of income	0.24
MTurkEarnings	$0 - 100 per month	0.06
	$101 - 250 per month	0.17
	$251 - 500 per month	0.30
	$500 - 1000 per month	0.33
	$1000 - 2000 per month	0.13
	$2000 - 3000 per month	0.02
DecisionsCareful		0.99
DecisionsRandom		0.04
DecisionsUnderstood		1.00
Repeated Choices Consistent		0.92
N		132

Table A9: Full Experimental Results with Interactions

	Implied Valuation ($)									
	All Observations					Subset Shown this Part First				
Part:	A	B1	B1	B2	B2	A	B1	B1	B2	B2
Variable										
Local	0.88	0.51	0.48	0.82	0.70	0.81	0.34	0.46	0.73	0.70
	(0.12)	(0.10)	(0.12)	(0.16)	(0.18)	(0.14)	(0.12)	(0.17)	(0.27)	(0.31)
Freshness		0.56	0.52				0.45	0.54		
		(0.12)	(0.15)				(0.16)	(0.22)		
Local:Freshness			0.04					-0.13		
			(0.09)					(0.14)		
Organic		0.40	0.38				0.39	0.45		
		(0.11)	(0.13)				(0.15)	(0.18)		
Local:Organic			0.01					-0.10		
			(0.07)					(0.09)		
Freshness:Organic			0.04					-0.02		
			(0.09)					(0.14)		
Flavor				0.71	0.78				0.95	0.99
				(0.14)	(0.16)				(0.31)	(0.34)
Local:Flavor					0.00					-0.02
					(0.09)					(0.16)
Size				0.51	0.49				0.48	0.46
				(0.13)	(0.14)				(0.23)	(0.28)
Local:Size					0.21					0.09
					(0.09)					(0.17)
Flavor:Size					-0.14					-0.05
					(0.10)					(0.20)
Participants	132	58	58	74	74	76	24	24	32	32
Observations	660	2320	2320	2960	2960	380	960	960	1280	1280

Valuation implied by logit coefficient estimates. Each regression uses the data from the specified part of the experiment. Standard errors in parentheses, computed using the delta method, clustered by participant.

C Innovation Exposes Hidden Tradeoffs

How does innovation affect hidden dimensions of quality? I quantify tradeoffs in the production function of wheat that have been exposed over the past century of innovation. Wheat is a useful case study for three reasons. Its primary uses have remained relatively stable, which makes it possible to compare quality over time.[25] Second, it is possible to track production choices, as the U.S. government has collected standardized statistics about the use of different varieties, which represent a large portion of wheat innovation. Third, most genetic innovation has occurred in the public domain, so there is detailed data on the merits of different production choices.

Innovation in Wheat Production

Wheat is a differentiated good. It has many dimensions of quality, related to milling and baking performance as well as nutritional value (with over 60 nutrients recorded in the most common nutrient database).[26] In particular, 43% of U.S. iron intake is from flour and cereal products, some of which are fortified (CDC, 2010). Traders have historically focused on quality relating to milling and baking performance. For example, Kaplan (1984) describes how eighteenth century traders in Paris sought out wheat with high baking quality, generally searching for kernels that were "light yellow or grayish with an almost translucent appearance, slightly convex with a shallow groove, and thin-shelled but hard, weighty, and dry."

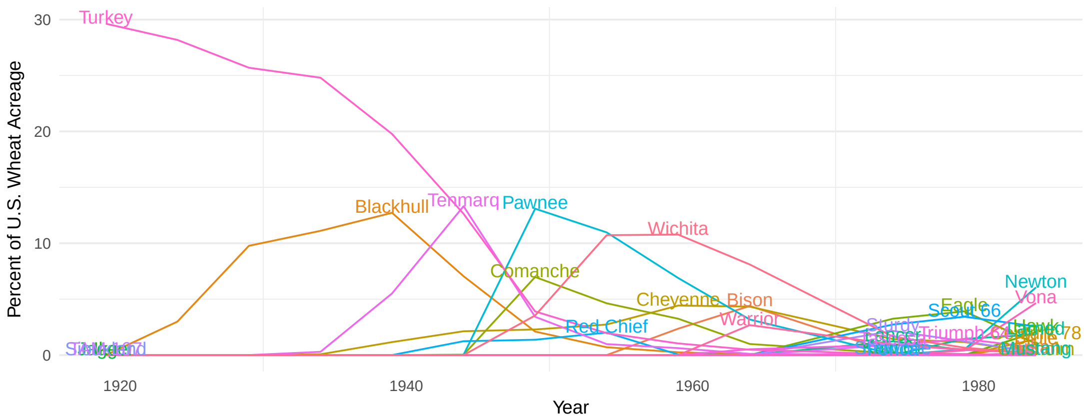
As transportation became cheaper and the U.S. market for wheat integrated, it became burdensome to track heterogeneous sacks of wheat from different farmers. In 1856, Chicago began treating this heterogeneous wheat as a commodity, developing grading standards to separate it into a manageable number of classes (Cronon, 1992). These evolved into national grading standards in 1923, which incorporate the grain's density as well as whether it is damaged or contaminated by foreign substances. Buyers often request additional measures, such as protein content, and may also consider a region or particular producer's reputation for producing grain well suited to baking. However, not all dimensions of quality are observed in grades, other metrics, or through experience: for example, mineral content has never typically been measured.

Over the past century, the technology to produce wheat has changed: a primary source of innovation has been the development of new genetic varieties (Olmstead and Rhode, 2008). Wheat varieties are primarily developed in the public sector at agricultural universities and

[25]This is contrasted with other crops such as corn, which with modern wet milling techniques is used to produce many more products than a century ago. As a result, it is difficult to compare the quality of different vintages of corn.

[26]U.S. Department of Agriculture's National Nutrient Database for Standard Reference.

Figure A3: Wheat Acreage by Variety



Source: USDA ARS for years where variety information was gathered.

offered to farmers in the form of seed (in 1979, 90% of U.S. land planted with wheat grew varieties developed in the public sector). Historically, variety development has pursued qualities of direct relevance to farmers (pest and disease resilience, and overall yields) and to farmers' customers (milling and baking quality). Figure A3 plots the historical use of a sample of prominent varieties: old varieties are replaced by new varieties.[27]

These innovations led to sustained increases in yields, as shown in Figure A4. Early varietal innovations (pre-1940) often adapted the grain to new areas or confronted emerging pests.[28] The 1940s and the decades following saw the introduction of shorter and semidwarf varieties which tolerate more fertilizer; these varieties produced a steady increase in aggregate wheat yields (Dalrymple, 1988).

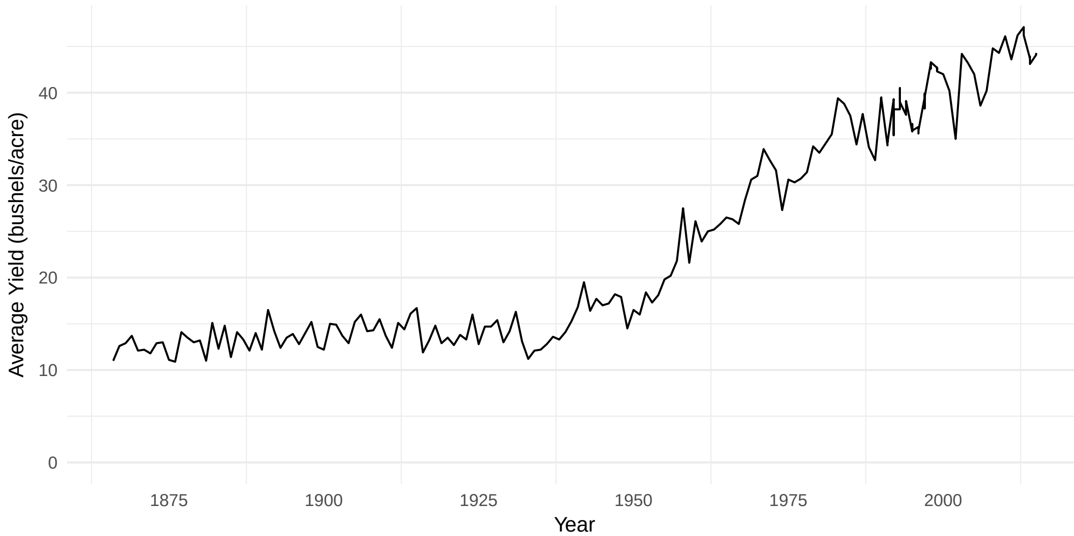
How has this innovation affected quality, both observed and hidden? I isolate the effect of production technology by summarizing results from randomized field trials that plant different vintages in a modern setting, holding other production choices fixed.

Tradeoffs between Observed and Hidden Quality

I combine results from three similar experiments conducted in Kansas at the KSU Agricultural Experimental Station, all designed to test for changes in hard winter wheat varieties introduced over the past century. In each experiment, a sample of prominent historical varieties was selected (shown in Appendix Table A10). Seed from selected varieties was sown in a randomized block design, and the resulting grain was measured across a set of dimensions. In each study, this design was replicated across at least two locations in Kansas with varying environmental characteristics over at least one season. Cox et al. (1989) tests 40 varieties

[27]See also Table A10 for the peak use of important varieties and dates of introduction.
[28]Although aggregate yields were relatively stable over this time, Olmstead and Rhode (2008) argue that yields would have declined without these innovations.

Figure A4: Wheat Yields in the U.S.



Source: USDA NASS.

in three sites over the 1986 and 1987 seasons, and measures milling and baking quality. Donmez et al. (2001) tests a subset of 8 of these varieties and 6 newer varieties in two sites, and measures yield (in the 1996 and 1998 seasons), and agronomic properties as well as susceptibility to falling over and infection by leaf rust (in the 1996 season). To measure susceptibility, an unprotected half of the plot was compared with a half that was protected (with fine netting and with a fungicide respectively). Garvin et al. (2006) analyzes the grain produced in Donmez et al. (2001) to measure mineral content. I average the results of each outcome across sites and seasons.

Figure A5 shows the evolution of agronomic characteristics. Plant height has decreased over time, with the advent of short and then semidwarf varieties. Newer varieties develop earlier, as shown by a decreasing heading date. The structure of the plant itself has also changed: newer varieties have longer, more dense spikes, with more kernels and spikelets per spike.

Figure A6 shows the evolution of different dimensions of quality. These genetic changes have made plants less likely to fall over (lodging has decreased) and less susceptible to leaf rust fungus. Overall, modern varieties lead to higher yields and biomass, which corresponds with a lower cost per volume. These improvements have been accompanied by overall improvements in milling and baking quality; these qualities are not incorporated into official grades but are sought after by buyers.[29] Modern varieties yield more flour per kilogram of wheat. On other measures, there is larger variation between new varieties which may suggest specialization for different purposes. There appears to be a slight decline in flour protein

[29] Absorption is a different measure of milling quality.

accompanied by increased variation. Several measures of baking quality have improved, including mixing time, loaf volume, crumb grain score, and a composite index.

However, there are tradeoffs between these observable improvements and dimensions of quality that were hidden at the time. As shown in the bottom row of Figure A6, Garvin et al. (2006) finds that modern varieties provide less mineral content, for copper, iron, zinc, and selenium. These results have been replicated experimentally (Guttieri et al., 2015) and are consistent with results from other experimental designs: Fan et al. (2008) finds declines in mineral content starting in the 1960s with the introduction of short straw varieties in Broadbalk Wheat Experiment, which has been running in the UK since 1843.[30]

Variety innovations have exposed these tradeoffs, and producers have exploited them. As shown in Figure A3, and also in Table A10, production has shifted from old varieties to newer ones that provide lower mineral content.

While these particular declines in wheat mineral content are likely to induce small changes in welfare, if changes have happened to these hidden dimensions, they may occur in other dimensions as well.[31] Next I consider evidence of nutritional changes in other crops.

Other Crops

There is evidence of nutritional changes in other agricultural products as well, though evidence is more tentative. Mayer (1997), Thomas (2003), and Davis et al. (2004) suggest that nutrient content has declined across different crops including fruits and vegetables. While it would be difficult to replicate the wheat experimental exercise with these crops due to changes in their uses, it is possible to do a more limited comparison of quality concurrent with the time that goods were produced. Figure A7 shows the distribution of changes in nutrient content between 1950 and 1999 for 43 garden crops based on USDA measures, from Davis et al. (2004).[32] This approach has substantial weaknesses and so should be interpreted with caution, but suggests dramatic declines in riboflavin and iron content across this sample of crops, as well as smaller declines in ascorbic acid, calcium, and vitamin A.[33]

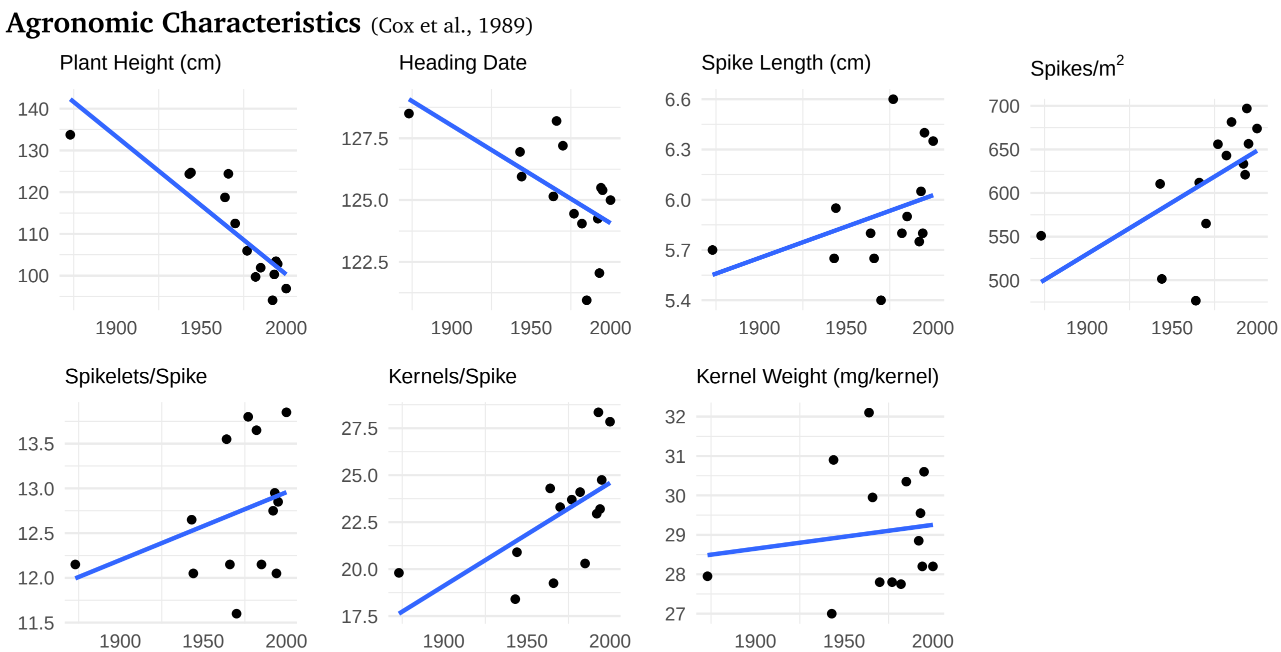
[30]There are two potential threats to this analysis. There may be complementarities between the variety and the environment (e.g., modern varieties are grown for different soil conditions); the experimental results I present partly address this threat by planting in at least two sites with different agronomic characteristics. Second, there may be complementarities between the variety and other production choices; for example, modern varieties are able to better tolerate fertilizer. However, for wheat, other relevant production choices have not changed dramatically; changes in typical fertilizer applications are unlikely to overturn the main results.

[31]Decreases in mineral content need not necessarily reduce welfare (some minerals are undesirable), but iron in particular is desirable for U.S. consumers: 16% of women and 7% of children have low iron stores (CDC, 2010). It would be relatively inexpensive to fortify diets with these missing minerals.

[32]Data is taken from USDA food composition tables, and corrected for moisture content following the procedure of Davis et al. (2004). I do not include standard errors as the 1999 tables include measures of precision but the 1950 tables do not.

[33]It is only possible to measure levels of historical quality for dimensions that were routinely measured at the time. And differences could arise from changes in measurement technology or the environment. For example,

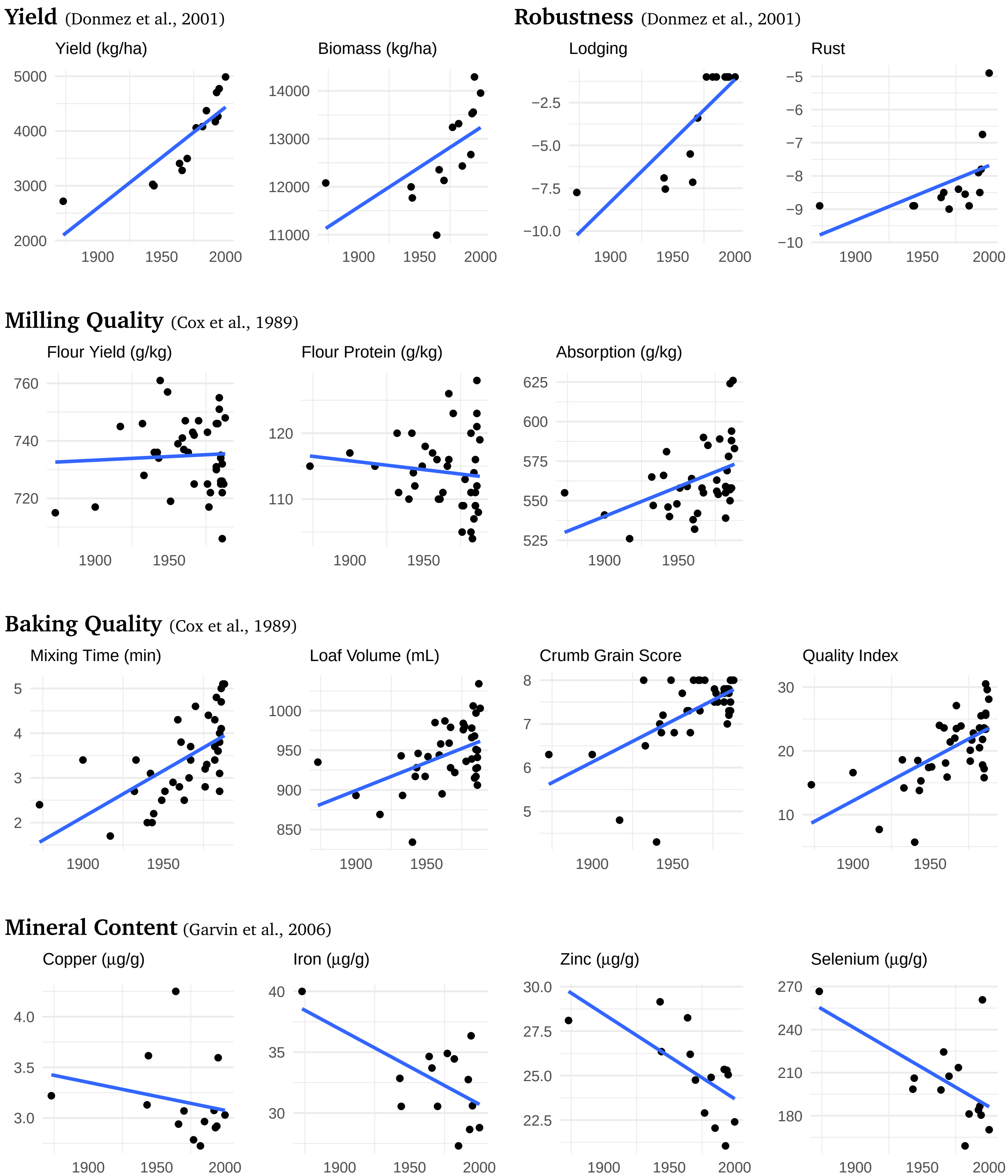
Figure A5: Agronomic Characteristics by Date of Variety Introduction, Controlled Field Trial



Sources: from randomized field trials completed in Kansas at two sites in 1996-1997 and 1998-1999 (Donmez et al. (2001) and Garvin et al. (2006)) and at three sites in 1986 and 1987 (Cox et al. (1989)).

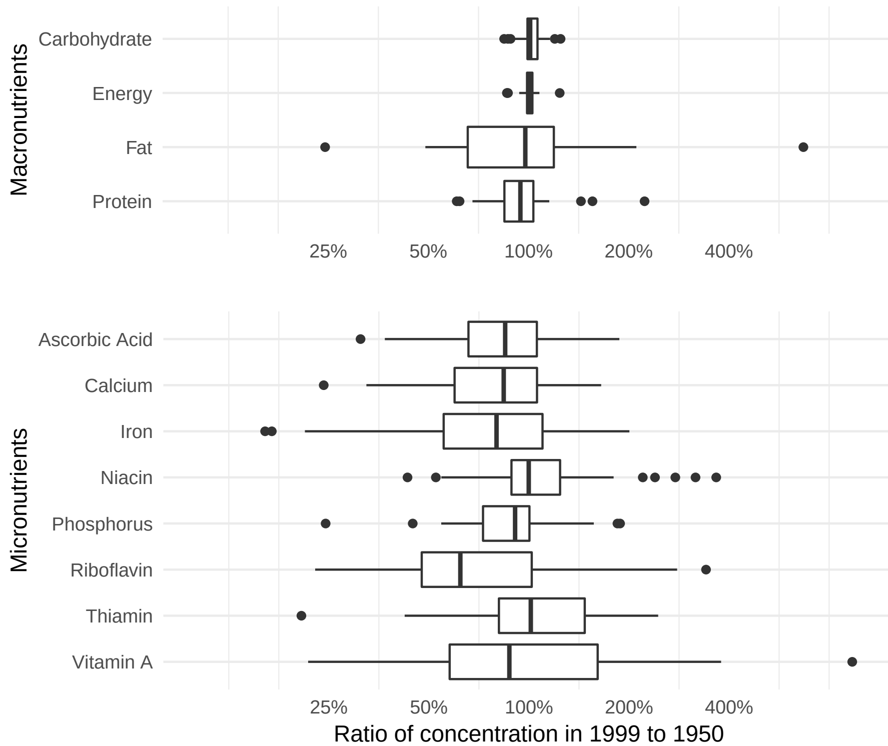
measures of iron are sensitive to how much soil is left on produce; measurement would be biased if produce was cleaned more thoroughly at different times.

Figure A6: Quality by Date of Variety Introduction, Controlled Field Trials



Sources: from randomized field trials completed in Kansas at two sites in 1996-1997 and 1998-1999 (Donmez et al. (2001) and Garvin et al. (2006)) and at three sites in 1986 and 1987 (Cox et al. (1989)). So that higher values are better, robustness measures for lodging and leaf rust are taken to be the negative of the more standard susceptibility measure.

Figure A7: Changes in Nutrients in 43 Garden Crops from 1950 to 1999



I report the ratio of the concentration of the nutrient in 1999 to that in 1950; a ratio of 100% represents no change. Each plot shows the range and quartiles of changes observed for each nutrient across 43 crops, as presented in USDA Food Composition Tables from 1950 and 1999. Source: moisture corrected nutrient content from Davis et al. (2004) for 43 garden crops commonly grown in home gardens.

The evidence in this section suggests that innovation can expose hidden tradeoffs. In these cases, affected minerals can be fortified into the diet. However, if innovation has changed these dimensions that have been measured, it may also change dimensions that are unmeasured. These observations accompany starker accounts where innovation has resulted in toxic side effects (such as DDT, BPA, and asbestos).

D Additional Background

Table A10: Wheat Varieties

Introduction	Variety	Peak Use			
Year		Year	Acreage (%)	Rank	Tested in
1873	Turkey	1919	29.6	1	Cox et al. (1989), Donmez et al. (2001)
1900	Kharkof	-	-	-	Cox et al. (1989)
1917	Blackhull	1939	12.7	2	Cox et al. (1989)
1932	Tenmarq	1944	13.3	1	Cox et al. (1989)
1933	Cheyenne	1959	4.4	3	Cox et al. (1989)
1940	Red Chief	1954	2.0	5	Cox et al. (1989)
1942	Comanche	1949	7.0	2	Cox et al. (1989)
1943	Pawnee	1949	13.1	1	Cox et al. (1989), Donmez et al. (2001)
1944	Wichita	1959	10.8	1	Cox et al. (1989), Donmez et al. (2001)
1949	Triumph*	*1979*	*1.4*	*4*	Cox et al. (1989)
1951	Ponca	1974	0.01	17	Cox et al. (1989)
1956	Bison	1964	4.4	2	Cox et al. (1989)
1959	Tascosa	1974	0.9	8	Cox et al. (1989)
1960	Warrior	1964	2.7	5	Cox et al. (1989)
1961	Kaw 61	1974	0.1	12	Cox et al. (1989)
1963	Lancer	1974	1.2	6	Cox et al. (1989)
1964	Triumph 64	1979	1.4	4	Donmez et al. (2001)
1966	Scout 66	1979	3.4	2	Cox et al. (1989), Donmez et al. (2001)
1967	Sturdy	1974	2.2	3	Cox et al. (1989)
1967	Shawnee	1974	0.1	13	Cox et al. (1989)
1970	Eagle	1979	3.9	1	Cox et al. (1989), Donmez et al. (2001)
1976	Larned	1984	1.8	5	Cox et al. (1989)
1976	Vona	1984	4.7	2	Cox et al. (1989)
1977	Newton	1984	6.1	1	Cox et al. (1989), Donmez et al. (2001)
1978	Centurk 78	1984	1.4	6	Cox et al. (1989)
1982	Arkan	1984	0.2	14	Cox et al. (1989), Donmez et al. (2001)
1982	Brule	1984	1.0	8	Cox et al. (1989)
1982	Hawk	1984	2.0	4	Cox et al. (1989)
1983	Chisholm	2004	0.2	36	Cox et al. (1989)
1984	Mustang	1984	0.03	17	Cox et al. (1989)
1984	Siouxland	2004	0.09	45	Cox et al. (1989)
1985	Stallion	-	-	-	Cox et al. (1989)
1985	TAM 107	2004	1.3	9	Cox et al. (1989), Donmez et al. (2001)
1985	TAM 108	-	-	-	Cox et al. (1989)
1985	Victory	-	-	-	Cox et al. (1989)
1986	KS831957	-	-	-	Cox et al. (1989)
1986	Norkan	-	-	-	Cox et al. (1989)
1986	Dodge	-	-	-	Cox et al. (1989)
1986	Century	-	-	-	Cox et al. (1989)
1987	TAM 200	-	-	-	Cox et al. (1989)
1988/1992	Karl/Karl 92	2004	1.5	7	Cox et al. (1989)/Donmez et al. (2001)
1993	Jagger	2004	30.9	1	Donmez et al. (2001)
1994	Ike	2004	0.9	14	Donmez et al. (2001)
1995	2137	2004	5.4	2	Donmez et al. (2001)
2000	KS941064-6	-	-	-	Donmez et al. (2001)

*: Cox et al. (1989) report using a 'Triumph 64' variety introduced in 1949. National wheat acreage based on US Department of Agriculture wheat variety surveys over the time period national data was collected (1919-1984). After this period I include three years (2004, 2009, 2012) where overlapping data is available from several major wheat producing states (OK, CO, NE, ND, KS, MT). '-' indicates no data available.