How do federal regulations affect consumer prices? An analysis of the regressive effects of regulation

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Abstract

This study is the first to measure the impact of federal regulations on consumer prices. By combining consumer expenditure and pricing data from the Bureau of Labor Statistics, industry supply-chain data from the Bureau of Economic Analysis, and industry-specific regulation information from the Mercatus Center's RegData database, we determine that regulations promote higher consumer prices, and that these price increases have a disproportionately negative effect on low-income households. Specifically, we find that the poorest households spend larger proportions of their incomes on heavily regulated goods and services prone to sharp price increases. While the literature explores other specific costs of regulation, noting that higher consumer prices are a probable consequence of heavy regulation, this study is the first to provide a thorough empirical analysis of that relationship across industries. Irrespective of the reasons for imposing new regulations, these results demonstrate that in the aggregate, the negative consequences are significant, especially for the most vulnerable households.

JEL codes: I18, D12, H23, L51

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1. Introduction

The 2012 *Code of Federal Regulations* includes more than a million individual restrictions, representing a regulatory burden that has grown by more than 28% over the past 15 years (Al-Ubaydli and McLaughlin 2015). Certain industries have experienced even faster regulatory growth over the same time period. For example, federal regulations related to highway and street construction increased by 94% over the past decade and a half. The natural gas distribution industry experienced a 109% rise in regulations, and the corresponding increase in the water and sewage industry was 125%.[1] As such, there is substantial variation in the types of regulations that exist both across and within industries—as well as across numerous regulatory agencies. While these regulations differ in their stated purposes and structures, they have consequences for both consumers and firms. The central question of this paper, which has been widely neglected by the literature, is how does greater regulatory intervention impact consumer prices and do those price changes affect socioeconomic groups differently?

Until 1971, most economists assumed that regulations were introduced with benevolent intentions to correct various market failures (i.e., concentrations of market power, externalities or asymmetric information). This *public interest* view of regulation was upended by Stigler's (1971) *interest group* theory of government, which postulates that competing interest groups (e.g., consumers and producers) pressure government regulators to craft rules that benefit them. Echoing the ideas of Olson (1965), Stigler (1971) predicts that smaller and better organized groups with much to gain will prevail over larger groups comprised of members with diffuse and less salient interests in the regulatory process. As such, industry frequently is the main

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[1] All estimates of the regulatory burden are from the RegData database of the Mercatus Center at George Mason University (North American Industry Classification System [NAICS] 2212—natural gas, NAICS 2213—water sewage, and NAICS 2373—highway and street construction).

beneficiary of new regulations. Building on this framework, Peltzman (1976) introduces the concept of self-interested regulators. Rather than simply being swayed by competing interest groups, regulators seek to maximize political payoffs (e.g., campaign contributions, expanded power/influence, and so on) in exchange for crafting rules favorable to the prevailing group. These rules can take the form of traditional economic regulation (such as price controls and barriers to entry/exit) or social regulation (e.g., occupational safety, consumer protection, environmental quality). Regardless of the form of regulation or the motivation driving regulators to promulgate new restrictions, one cannot deny that compliance with regulations translates into higher costs for would-be entrants and/or incumbent businesses, which ultimately increases prices for consumers. In fact, McKenzie and Macaulay (1980) argue that many regulations are intentionally wasteful and benefit neither firms nor consumers, but are instead designed to inflate the costs of producing private goods, while simultaneously reducing the relative prices of public goods, thereby stimulating the demand for them. Ultimately, the fulfillment of these demands expands the size of the government and the scope of its activity in the economy. The core hypothesis of this paper is that if this rise in prices occurs, regulatory growth is unlikely to affect all consumers equally. Because the spending patterns of high- and low-income families differ, regulations that increase prices in a particular market sector often have disparate socioeconomic impacts.

Recent information from the Consumer Expenditure Survey (CE) reveals that households just below the poverty line spend substantially larger percentages of their incomes on transportation and gasoline, utilities, food, and healthcare than do high-income households (Goldstein and Vo 2012). To the extent that regulations raise prices, regulations will cause regressive effects if they are concentrated in the economic sectors where low-income households spend the most. The purpose of this study is to analyze the potential regressive effects of federal regulations—first by documenting differences in consumer spending patterns across income levels and then by examining how regulatory growth has affected the prices of goods and services for consumers across the income distribution spectrum.

By using detailed expenditure and pricing data from the Bureau of Labor Statistics (BLS), we first assess whether meaningful differences can be observed in the spending habits of average consumers from different income quintiles. We join these data with information on regulatory restrictions by industry, available from the RegData database published by the Mercatus Center at George Mason University, to determine the effect of regulatory expansion on consumer prices. Our results are twofold. First, growth in federal regulations is associated with higher consumer prices overall. Specifically, a 10% increase in total regulations leads to just under a 1% (0.890%) increase in consumer prices. Second, we find that households from the poorest income groups experience the highest overall increases in the prices they pay.

2. Background on the costs of federal regulations

Measuring the full costs of federal regulations is difficult. The Regulatory Right-to-Know Act of 1999 requires the Office of Management and Budget (OMB) to publish an annual report detailing the costs and benefits of major federal regulations. In its May 2014 report, OMB estimates the annual cost of regulations to be between $74 billion and $110 billion.[2] However, OMB openly acknowledges that this estimate is far from a full accounting of all federal regulatory costs. For example, the report excludes costs associated with rules that are more than

[2] This cost estimate is in constant 2014 dollars, as evaluated by Crain and Crain (2014). The actual estimate cited in OMB (2014) is $68.5 billion to $101.8 billion, in 2010 dollars.

10 years old and rules that are not defined as *major* (i.e., rules having an annual economic effect of less than $100 million).

Crain and Crain (2014) estimate that the true comprehensive cost is more than $2 trillion,[3] including all regulations and accounting for many indirect costs, such as reduced economic productivity, that are absent from OMB's analysis. The authors note that some portion of these costs is passed on to consumers in the form of higher prices, although they neither model nor empirically estimate the price increases.

Several papers address the potentially harmful unintended consequences of regulations. McLaughlin and Williams (2014) outline some of the adverse outcomes related to regulatory accumulation, or the "buildup" of old or obsolete regulations inherent in the US regulatory system, including slower rates of economic growth, reductions in new business formation, and weaker international competitiveness. A substantial literature exists documenting the adverse consequences of regulation in both the United States and abroad.

For example, Dawson and Seater (2013) examine the specific impact of federal regulations on economic growth and estimate that since 1949, regulatory intervention has significantly reduced the rate of economic growth, resulting in an accumulated GDP loss of $38.8 trillion by 2011. Other papers report a negative relationship between regulatory expansion and economic productivity, including Nicoletti and Scarpetta (2003), Djankov, McLiesh and Ramalho (2006) and Crafts (2006). Gørgens, Paldam and Würtz (2003) explore the possibility of a nonlinear relationship between regulation and economic growth and find that the bulk of the effect stems from a transition from moderate to heavy levels of regulation.

[3] This estimate is in 2014 dollars.

One key channel through which federal regulations are likely to affect economic growth is by creating significant barriers to new business entry. Benson (2004) discusses this barrier as a significant opportunity cost of regulation. Empirical studies find that higher regulatory compliance costs lead to slower rates of new business entry in both Europe (Klapper, Laeven and Rajan 2006) and the United States (Fisman and Sarria-Allende 2004). Ciccone and Papaioannou (2007) examine the time it takes new businesses to comply with regulatory entry requirements and find that reducing red tape is associated with larger numbers of start-ups.[4]

Social regulation, which includes a wide array of non-economic regulations (e.g., consumer protection rules, workplace safety regulations, environmental rules) is a significant source of federal regulatory restrictions.[5] Third-party advocacy groups often play pivotal roles in the passage of new social regulations. The pioneering work of Yandle (1983) keenly demonstrates that coalitions of groups with aligned goals ("bootleggers and Baptists") may work together to promulgate new regulations. Dolar and Shughart (2007) apply this concept to financial services, and chronical how anti-Wall Street groups ("the Baptists") and large banks ("the bootleggers") jointly supported strict measures ostensibly designed to curb money laundering and the movement of funds to finance terrorists. The resulting high compliance costs reduced competition for the big banks as many smaller banks struggled to comply. Interestingly, Paul and Schoening (1991) demonstrate both theoretically and empirically that the participation of interested third parties seeking monetary payoffs (unlike "the Baptists" described above), leads to increases the prices of regulated products. It is worth noting that although third-party advocacy groups can successfully lobby for new restrictions on business, this form of regulation

[4] For other examples detailing the relationship between regulation and economic growth, see Ardagna and Lusardi (2010) and Benson (2015).
[5] For a breakdown of federal regulations by type, see the Mercatus Center's "How the Top Ten Regulators of 2012 Changed over Ten Years" (http://regdata.org/how-the-top-ten-regulators-of-2012-changed-over-ten-years/).

can also result from industry capture, whereby a subset of firms within an industry supports more stringent standards because they (and not their competitors) have cost advantages in compliance (see, for example, Shughart 2003 and Hoffer *et al.* 2015).[6]

Focusing on the costs associated with one form of social regulation, environmental quality, a significant body of literature examines the Clean Air Act, the Clean Water Act, and their later amendments. Becker and Henderson (2000) show how the Clean Air Act altered businesses' decisions regarding the construction, location, and size of new plants. In response to the new regulations, firms were more likely to build smaller plants in low-pollution areas. Although firms' decisions complied with environmental legislation, the costs of building inefficiently sized plants in suboptimal locations were significant.[7] Greenstone (2002) documents substantial job losses, reductions in capital investments, and lower outputs as a result of the same regulations. Hazilla and Kopp (1990) emphasize the importance of accounting for social costs when evaluating the effects of environmental regulations, rather than simply counting private expenditures. They highlight the potential for spillover effects outside the industry directly affected by the regulations and note that the social costs of regulation likely increase through time.[8]

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[6] For example, if regulatory compliance raises fixed costs, larger producers would benefit over smaller rivals by spreading said costs over larger volumes of output. Likewise, if newer and more efficient producers are better able to comply with new directives, they may push for tougher standards to squeeze the operators of older facilities who would be forced to make significant investments to stay in business. Regardless, the result is larger market shares and less competition for the advantaged producers.

[7] For related research detailing the effects for specific industries, see Becker and Henderson (2001). Additionally, Becker (2003) examines how local community attributes predict the level of investment in pollution abatement.

[8] They estimate that while the Clean Air and Water acts created the largest burden for the energy sector, every production sector experienced some rise in costs, many through secondary effects. The insurance and finance sectors, for example, do not bear direct cost increases from environmental regulations. However, production costs in even these sectors rise as a result of increased factor prices.

An additional consequence of federal regulations is their potential regressive effects. While a substantial body of literature addresses the regressive effects of taxation,[9] only a few studies explore the distributional consequences of regulation. The early literature focuses on the regressive effects of environmental quality regulations. The earliest of these papers, Dorfman and Snow (1975), estimates the incidence of costs for the US environmental protection program (as it existed in 1973), for the years 1972, 1976 and 1980. They find that the compliance costs were mildly regressive in 1972, but grew in regressive intensity as time elapsed. Gianessi *et al.* (1979) show that while the federal Clean Air Act of 1970's standards applied nationwide, neither the costs nor the benefits of improved air quality pollution were distributed evenly. The incidence of compliance costs were highly regressive, with households in the poorest income group spending on average 8.2% of their annual income compared to 1.8% for the highest income group. However, overall benefits were progressive, with the lowest income decile receiving benefits equal to 8% of household income, compared to 1.3% for the highest income group. On balance, the net benefits (i.e., benefits minus direct costs) of compliance were mixed. With respect to automobile emission standards, net benefits of compliance were universally negative and regressive, ranging from -3.1% of household income for the poorest group and increasing to -0.4% for the highest income group. The overall net benefits of all air quality regulations were highest for the poorest income group (-0.2% of income), but were mildly regressive for the remaining income groups – i.e., households in the next poorest income decile received net benefits of -0.9% of income, with this estimated figure gradually rising to -0.5% for the highest income decile. The following year, Gianessi *et al.* (1980) explore the distributional impact of Clean Water Act of 1972 regulations on US families, and finds that lower income

[9] See Poterba (1991) for an analysis of gasoline taxes, Wier *et al.* (2005) for an analysis of carbon dioxide taxes, and Borren and Sutton (1992) for an examination of cigarette taxes.

families bore a disproportionate burden of the short-run compliance costs. Finally, Robison (1985) estimates the industrial pollution abatement cost burden faced by a wide array of income groups in 1973 and 1977. In both years, abatement costs were estimated to be highly regressive.

Recently, researchers have studied the regressivity of a broader array of regulations. For example, Crain and Crain (2010) analyze the effects of regulations on businesses and find that small firms bear disproportionate shares of compliance costs. Thomas (2012) argues that many health and safety regulations are regressive because they often target risks that reflect the preferences of high-income households. Relative to their low-income counterparts, high-income households have stronger preferences for reducing low-probability risks that are costly to mitigate. When these risks are addressed by regulations, all market participants (regardless of income) bear the cost—in the form of higher prices for consumers and lower wages for workers. Thomas contends that regulatory costs are disproportionately borne by low-income households, inasmuch as they are obliged to pay for higher levels of care for human health and safety than they would in the absence of regulation. In addition, these costs potentially crowd out private risk-reduction spending by low-income households.

Miller (2012) allows for the possibility of distributional effects in her analysis of the federal energy conservation regulation for new residential dishwashers. The Department of Energy, which issued the new regulation in 2012,[10] estimated that it would raise dishwasher prices by 13%. Interestingly, Miller reports that the breakeven point for a consumer to recover a higher dishwasher price from energy savings is 11.8 years of operation, which is longer than (or near the end of) the average 9-to-12-year useful life of a new residential dishwasher. Miller

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[10] Department of Energy, Direct Final Rule: Energy Conservation Standards for Residential Dishwashers, RIN No. 1904-AC64, May 30, 2012, https://www.federalregister.gov/articles/2012/05/30/2012-12340/energy-conservation-program-energy-conservation-standards-for-residential-dishwashers#h-12.

calculates that the breakeven point for senior adults and low-income households exceeds 13 years, suggesting that these consumers are harmed even more than other households by the energy efficiency regulation.

While studies such as Miller's examine the effects of specific regulations on prices in particular industries, no study to date offers a comprehensive analysis of the impact of regulations on consumer prices in general. This paper contributes to the literature by estimating empirically the relationship between regulatory growth and consumer prices, as well as by examining the extent to which regulations are regressive. We begin by constructing a simple theoretical framework to demonstrate the relationship between regulations and price changes and to show how regulations might affect consumers of varying income levels differently. We then match quintile-based basket weights and prices for over 60 consumer expenditure categories from the BLS with regulatory restrictions from the RegData database. Using the matched panel dataset, we estimate the regressive impact of federal regulations on consumer prices. Care is taken to ensure that our results are properly identified and robust to differences in model specification and estimation methodology.

3. Theoretical framework

Before we begin our empirical analysis, we present a simple theoretical model to illustrate how we envisage regulation affecting prices and consumers' spending patterns. Consider an economy with $n \geq 2$ consumers who are distinguished by their incomes. Consumer *i* spends part of her income on a regulated commodity, x_i, with the remainder of her income spent on other (unregulated) commodities. The demand function for the regulated commodity is $x_i(p, m_i)$, where p is the price of the regulated commodity and m_i is consumer i's money income. The demand for all goods is assumed to be decreasing in price and increasing in income.[11]

The regulated commodity is produced by a firm with the supply function $x(p, R)$, which is increasing in price and decreasing in the level of regulation R, the latter relation owing (for example) to regulation raising the cost of production. Equilibrium requires that

$$\sum_i x_i(p, m_i) = x(p, R). \tag{1}$$

That is, aggregate consumer demand for the regulated commodity must equal the quantity supplied by the firm.

From the above framework we obtain the following predictions (see Appendix A for the mathematical details):

Prediction 1: *If demand for the regulated commodity with respect to income is inelastic*, *then lower-income consumers spend larger shares of their incomes on the regulated commodity than do higher-income consumers*.

Commodities that are considered to be necessities or essential in nature (e.g., utilities, food, healthcare) tend to be subject to more regulation than other types of commodities. As the demand for necessities tends to be both price and income inelastic, it follows that lower-income consumers will spend relatively more of their incomes on the regulated commodity.

Prediction 2: *More regulation increases the price of the regulated commodity*.

The intuition behind Prediction 2 is simple: more regulation reduces the supply of the regulated commodity (by raising production cost), *ceteris paribus*; thus, its price must rise to clear the market.

[11] We place no restrictions on the precise form of the demand function, though for simplicity we assume that it generates constant own-price and income elasticities.

Prediction 3: *If demand for the regulated commodity with respect to both income and price is inelastic*, *then an increase in regulation causes lower-income consumers to reduce their spending on other commodities by proportionally more than it does for higher-income consumers.*

The intuition for Prediction 3 follows that for Predictions 1 and 2. Lower-income consumers spend proportionately more of their incomes on the regulated commodity, and more regulation increases its price. As the most heavily regulated commodities tend to be necessities, and necessities tend to be both income and price inelastic, an increase in price hurts lower-income consumers more in the sense that their spending on other commodities must fall by a greater proportion.

Regulation provides some well-known and clear-cut benefits, such as ensuring that commodities satisfy certain quality standards and are safe for consumption. But as the above analysis suggests, regulation also can have adverse effects falling disproportionately on lower-income consumers. It is these effects that we explore in our empirical work.

4. Differences in spending patterns across income groups

We begin our analysis by evaluating Prediction 1 of our theoretical model, which posits that low- and high-income households differ in their spending habits. In particular, low-income households should spend larger percentages of their income on more heavily regulated goods and services relative to high-income households, if the demand for these goods is inelastic. To examine this prediction empirically, we combine two data sources: household expenditure and pricing data by good/service category from the BLS and industry-specific data on regulatory restrictions from the RegData database.

4.1 Household expenditure data

The Consumer Expenditure Survey (CE) is based on quarterly interview surveys, conducted by the Bureau of Labor Statistics, of approximately 7,000 US households. It is constructed as a rotating panel, in which each household is interviewed once every three months for five quarters and then is dropped from the survey. The survey contains information related to household income levels and demographic characteristics, as well as detailed data that describe household expenditures.

The CE dataset is organized by the Universal Classification Codes (UCC) system, which consists of six-digit codes that categorize goods and services into specific purchase groups. Households are queried about the details of their monthly spending habits. Each purchase is recorded and labeled with an appropriate UCC. The CE also collects income data for each household, enabling the examination of expenditure habits by income level. Using this micro dataset, the BLS constructs expenditure share tables by pretax income quintiles for approximately 70 broad categories (known as item strata), which vary in number and composition by year.[12] Because of this variation in coverage, we limit our focus to the 61 expenditure categories that span the full sample period, excluding any non-consumption household spending (e.g., charitable contributions, life insurance payments, and retirement contributions).

The BLS also publishes "stub files", which are mappings describing how the underlying UCC-coded expenditures are aggregated from the micro CE data to form the annual expenditure

[12] Data available at http://www.bls.gov/cex/csxshare.htm. Given the minor variation in categories by year, we select those categories with consistent coverage over the sample period.

categories described above.[13] This mapping ultimately enables us to aggregate UCC-matched regulations onto the smaller set of 61 annual expenditure categories (described in greater detail below). The BLS also publishes comprehensive Consumer Price Index (CPI) values for each of the corresponding aggregate expenditure categories described above, which easily facilitates the matching of expenditure shares and prices.[14]

4.2 RegData

While *regulations* can be used to refer to the guidelines published in the *Code of Federal Regulations*, it is important for our empirical work that we define the term precisely. Our regulation measures come from RegData, the Mercatus Center's database of industry-specific federal regulations. RegData is unique in its method of measuring regulatory burdens. It analyzes rules and guidelines published in the *Code of Federal Regulations*, but instead of reporting page counts or numbers of rules, it counts each specific binding restriction that appears in the texts of regulatory policies. Each time a policy includes a word indicating an obligation, such as *must* or *shall*, that word is counted as a restriction.[15] These restrictions are weighted by their industry relevance and summed to produce a regulatory index value.[16] Regulatory index values are reported by industry and by year, so it is possible to track regulatory restrictions within a particular industry over time. All our empirical calculations and estimates of "regulations" refer to this regulatory index from RegData.

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[13] We use the 2010 Diary stub file (Dstub) to map UCC codes onto the aggregate categories. Documentation pertaining to the CES and the stub files are available at http://www.bls.gov/cex/pumd/documentation/documentation14.zip. For missing or sparsely covered expenditure categories, we included additional, related UCC mappings.

[14] For each year, we use the year-end annual price averages from the December "CPI Detailed Report", available at http://www.bls.gov/cpi/cpi_dr.htm.

[15] Five words are coded as restrictions in RegData: *shall*, *must*, *may not*, *prohibited*, and *required*.

[16] For details on the methodology of calculating measures of regulation, see www.regdata.org/methodology.

RegData reports regulations by two-, three- and four-digit codes of the North American Industry Classification System (NAICS). To combine this information with the expenditure and consumer price data from the BLS, we link NAICS codes to UCCs using commodity input-output tables from the Bureau of Economic Analysis and the Consumer Expenditure/Personal Consumption Expenditure Concordance from the BLS.[17]

We have approximately 350 unique UCCs for each year. To create broader spending categories—and to facilitate an eventual examination of the effect of regulation on prices—we collapse UCCs into the aggregate expenditure categories used by the BLS. Using the BLS's CE aggregation scheme, we match the underlying UCC codes from the BLS's consistent 61 expenditure categories with our regulation dataset indexed by UCC code. Our combined dataset (793 observations) includes data for five income quintiles, spanning the 2000–2012 period. Furthermore, our measures of regulatory burden include both *direct regulations*, which capture restrictions affecting a good or service itself, and *input regulations*, which capture restrictions affecting the supply chain of inputs for a particular good or service (see Appendix B for details). The variable *total regulations* is the sum of direct and input regulations.

4.3 Consumer expenditure patterns

Table 1 shows the percentage of spending for each income quintile in categories with very high and very low levels of regulation. These numbers represent average values for each income quintile spanning the 2000–2012 period. Households in the highest-income quintile spend 54.5% of their incomes in the 25 most heavily regulated expenditure categories, where regulations for goods and services are measured directly (excluding input regulations). The corresponding

[17] For a detailed description of the methodology mapping regulations from the NAICS space onto goods and services in the UCC space, see Appendix B.

number for the lowest-income households is 60.2%, which is 10% more than high-income households. Including all regulations, the difference is about 12%.

[Table 1 here]

An opposite pattern is evident when comparing expenditures in the *least regulated* expenditure categories. The highest-income group allocates 32.19% of its total spending to goods and services subject to the fewest direct regulations, while the bottom-income quintile spends 25.64% of its total expenditures in the same category. Total regulations reflect the same patterns, with high-income households spending more (38.6%) in lightly regulated areas than low-income households (31.9%).

Table 2 presents the expenditure categories for which the difference in expenditure allocations between the bottom- and top-income quintiles is greatest.[18] These are areas in which the lowest-income families allocate larger shares of their overall spending than do higher-income families. These categories contain rent and utilities, including electricity, telephone services, and audio and visual equipment and services. Households from the lowest-income quintile spend more than five-and-a-half times as much on rented dwellings than households from the highest-income quintile, as a percentage of total expenditures.[19] They spend almost 85% more on electricity as a percentage of total expenditures and 50% more on telephone service. Other categories in which the poorest households spend larger proportions

[18] For a complete list of the top-20 expenditure categories and their corresponding direct and total regulation ranks for each of the five income quintiles, see Appendix B.
[19] Note that spending for each quintile is reported as a percentage of overall total expenditures for each income group. The level of total spending in most categories is greatest for households in the top quintile.

of their incomes are drugs and medical supplies, medical insurance and miscellaneous food items.

[Table 2 here]

To explore the regulatory restrictions that apply to these categories, Figure 1 plots annual direct regulations for each of these expenditure categories from 2000 to 2012.[20] For most categories, a general upward trend in regulations is evident over the sample period. Exceptions are the cigarette industry, which has experienced a downward trend (at least until recently), and the category that includes medical services and insurance, which experienced a sharp initial drop in regulations, followed by a steep increase. The category containing rented dwellings also experienced a recent spike in regulations, following earlier variations across time. Most of the expenditure categories that capture basic utilities show substantial growth in regulations: direct regulations for electricity, telephone service, and audio and visual equipment and services all increased by 33% to 37%. Regulations in the gasoline industry grew by 33%. The largest increase occurred in the drugs and medical supplies category, which experienced an almost 90% rise in direct regulations.

[Figure 1 here]

Taken together, these data support the argument that important differences exist in consumer spending patterns by income groups. We find that, relative to the wealthiest

[20] RegData contains no direct federal restrictions for the nonalcoholic beverages expenditure category, so we include no corresponding graph of changes in regulation for this category.

households, the poorest households spend larger percentages of their incomes on goods and services that are more heavily regulated and smaller percentages of their incomes on goods that are less regulated. Particularly large differences are evident in spending patterns for utilities, including natural gas, electricity, and cable or satellite television service. The regulatory burden on these industries has increased sharply over time. In most cases, the increases have outpaced the overall average growth rate of all regulations.

5. Calculating price changes by income group

Given the established differences in spending habits across income groups, we seek to determine whether growth in regulations has a disproportionately negative effect on low-income households in the form of higher prices for goods and services, which comprise a large share of their expenditures. To explore these potential regressive regulatory effects, we employ the detailed Consumer Price Index data for each expenditure category.

[Table 3 here]

Table 3 contains the names of each expenditure category, the average basket weight by income group, and the direct, input, and total regulations for each expenditure category. We also use the expenditure basket weights to construct annual aggregate weighted regulation series for each income group:

$$Reg_t^h = \sum_i w_{it}^h \cdot Reg_{it}, \tag{2}$$

where w_{it}^h are expenditure basket weights equal to the proportion of spending in year t on expenditure category i by households in quintile h ($h = 1, 2, \dots, 5$), and Reg_{it} are the regulations that apply to expenditure category i in year t. Table 4 reports the weighted regulations that apply to the full all-households group.

[Table 4 here]

By combining the basket weights and price data, we construct two alternative price indexes for each income group. The first is a classic Laspeyres price index, whereby for each income group (h), fixed basket weights from the base year (2000), denoted by $\bar{w}_{i,2000}^{h}$, are multiplied by their corresponding current-year category prices (P_{it}) and summed over the expenditure categories (indexed by i) to derive the following index:

$$P_t^{h,Laspeyres} = \sum_i \bar{w}_{i,2000}^{h} \cdot P_{it} \tag{3}$$

The widely used Laspeyres price index suffers from a number of well-known problems, most notably substitution bias. To overcome this shortcoming, we calculate the following chained price index:

$$P_t^{h,chained} = P_{t-1}^{h,chained} \times \prod_i \left(\frac{P_{it}}{P_{it-1}}\right)^{\frac{w_{it}^{h}+w_{it-1}^{h}}{2}}. \tag{4}$$

Table 5 reports the aggregate price indexes for both of the foregoing methodologies. Interestingly, regardless of the index used, the rate of price increases is highest for the poorest households, declining as incomes rise. This finding is consistent with Kaplan and Schulhofer-Wohl (2016), who use the 50,000 household Kitts-Nielsen Consumer Panel (KNCP) dataset and discover that low-income households (on average) experience higher inflation rates.

[Table 5 here]

[Figure 2 here]

6. The effect of regulations on consumer prices

6.1 GMM estimation results

Figure 2 provides a scatter plot of the weighted total regulations for each of the five income groups against their corresponding group-specific chained price series. Clearly, a strong positive correlation exists between total regulatory burden and total prices. That said, both prices and regulations trended upward over the sample period (2000–2012), so it is important explicitly to control for this common trend to rule out any spurious correlation. To do this, we compare the growth rate of prices over time against the growth rate of regulations.[21] To ensure that the regulation-consumer price results are properly identified, and robust to the inclusion of alternative control variables, we insert lagged regulation growth into a standard Phillips curve model (see Stock and Watson 2008):

$$p_t^h = \alpha^h + \beta reg_{t-1}^h + \rho p_{t-1}^h + \mathrm{A(L)}X_t + u_t^h, \qquad (5)$$

where p_t^h is the log first difference of the chained price series for household h, α^h are unique intercepts for each income group, reg_{t-1}^h is the logged first difference of the total regulations series for household h lagged one year, X_t includes the national unemployment rate and output gap, and the lag operator A(L) returns the contemporaneous and one-period lagged values of X_t; u_t^h is a mean zero error term.[22] To ensure that the results are robust and that inclusion of a one-period lag $(t-1)$ of prior regulatory growth is appropriate, we perform a lag-selection exercise that includes every combination of the following three variables and are added to a simple first-order autoregressive model of price increases: current regulatory growth (t), a one-period lag

[21] In practice, we transform the price and regulation data by taking their natural logarithm and first differencing each series. This calculation effectively yields the growth rate of each series.

[22] The annual civilian unemployment rate and the annual real gross domestic product (billions of chained 2009 dollars) are from the St. Louis Federal Reserve FRED Database (https://fred.stlouisfed.org). Using the Hodrick-Prescott filter ($\lambda = 6.25$), real output is split into a trend and cyclical component. The cycle is then normalized by the trend component and expressed as a percentage, thus yielding the output gap.

($t-1$) of regulatory growth, and a two-period lag ($t-2$) of regulatory growth.[23] Both the Akaike and the Schwarz criteria are minimized when only a one-period lag of regulation growth (reg_{t-1}^{h}) is entered. This result supports our earlier theory of a natural gestation period between the publication of new regulatory restrictions and their measurable impact on prices. After the impacted production processes have been altered to comply with new regulatory dictates, an associated jump in the price of these goods and services is found. Moving forward, these regulations do not promote additional price hikes as their effect already has been captured in the change in the price level of the affected goods and services, suggesting that longer lags of regulatory growth should not have statistically significant effects on the current growth rate of prices.

[Figure 3 here]

Figure 3, which plots the average price increases for all households, reveals a sharp deflationary drop in 2008, with the series falling from about 4% in 2007 to nearly -1% in 2008. This clear structural break in the price index (and hence negative spike in the growth rate) likely introduces downward bias in the estimated AR(1) coefficient on price increases. Therefore, a dummy variable for 2008 to correct the break introduced by the Great Recession is also added to Equation (5).

Equation (5) is a dynamic fixed-effect panel model. Unfortunately, standard fixed effects methods that utilize a within transformation (or random effects methods) yield biased coefficient

[23] The lagged selection model is a simple AR(1) time series framework with common intercept term: $p_t^h = \alpha + \beta(L)reg_t^h + \rho p_{t-1}^h + u_t^h$. Without exception, current regulatory growth and the two-period lag of regulatory growth are statistically insignificant in every variant in which they appear.

estimates in such models. Therefore, we first utilize Arellano and Bond's (1991) generalized method of moments (GMM) estimator, which was specifically developed to estimate dynamic fixed-effect panel models. A brief sketch of this estimation procedure will follow; those interested in a fuller exposition should see Arellano and Bond. To begin, Equation (5) is first-differenced to eliminate the income-group fixed effects. Next, a suitable instrument set is constructed, consisting of lagged predetermined endogenous variables expressed in levels (i.e., $p_{t-2}^h, p_{t-3}^h, p_{t-4}^h$) and the exogenous variables expressed in first differences (i.e., Δreg_{t-1}^h).[24] For the Arellano and Bond estimator to yield consistent and efficient estimates, the model's errors cannot be autocorrelated; that is, $E(u_t^h u_s^h) = 0$ for $s \neq t$. Following Arellano and Bond, we use the Sargan test for overidentifying restrictions, which tests the validity of moment restrictions implied by the instruments. Under the null hypothesis that the moment restrictions are valid (which implies the absence of second- or higher-order autocorrelation), the test statistic is asymptotically chi-square distributed.

Estimation results for Equation (5) are provided in Table 6. Because Lanne and Luoto (2014) find the most common control variables (i.e., labor's share of total income, the output gap, and the unemployment rate) are not empirical drivers of US inflation, as a preliminary baseline we first estimate Equation (5) without the unemployment rate and output gap (see column (1)). The coefficient on lagged regulatory growth is statistically significant, equaling 0.0687 and implying that a 10% increase in total regulations is associated with a rise in consumer prices by an additional 0.687%.[25] Furthermore, the Sargan test statistic for Equation (5) is equal to 4.95 with

[24] Arellano and Bond (1991) specify the use of all predetermined lagged endogenous variables, whereas we follow the common practice of using less than the full set of lagged variables (i.e., we use periods $t-2$, $t-3$, and $t-4$ inflation rates, but not period $t-5$ or before). We did experiment with larger instrument sets that included more lags, but the results (not reported in this paper but available on request) were nearly identical.
[25] We use White (period) robust standard errors throughout unless otherwise specified.

an associated *p* value of 0.18. Therefore, we cannot reject the null hypothesis that the overidentifying restrictions are valid. Therefore, the *n*-step GMM estimation results reported below are both consistent and efficient.[26]

[Table 6 here]

Column (2) of Table 6 reports the results for the preferred specification of Equation (5), which includes the full set of control variables. The coefficient on lagged regulatory growth is statistically significant and nearly double the initial estimate reported in column (1), equaling 0.1258. This result implies that a 10% increase in total regulations increases consumer prices by a hefty 1.258%. The coefficient on lagged price growth is negative and statistically significant, consistent with the dampened oscillations depicted in Figure 3. The coefficients on unemployment are contradictory, as one would expect higher unemployment to reduce inflationary pressure (i.e., both coefficients should be negative). The coefficient on lagged unemployment is negative and statistically significant (-0.0093) but is nearly exactly offset by the positive coefficient on current unemployment (0.0097). Likewise, the coefficient on the current output gap is positive as one would expect (0.0177), but is partially offset by the negative coefficient on the lagged output gap (-0.0093). Not surprisingly, the Great Recession dummy variable is negative and statistically significant (-0.0249). Although these results are somewhat unexpected, it is important to stress that the output gap and unemployment are included to help appropriately identify the impact of regulations on consumer prices. Furthermore, the estimated

[26] The original Arellano and Bond (1991) estimator involves two steps, whereby an initial consistent estimate of the dynamic panel yields residuals that are used to construct a GMM weighting matrix, that is, used to more efficiently re-estimate the dynamic panel. Our software package, Eviews, iteratively repeats this process, each time updating the GMM weighting matrix until convergence is achieved. The result is a more efficient estimator than that proposed by Arellano and Bond. If the weighting matrix is not invertible, the 1-step matrix is used instead.

impact of past regulations on current price increases is not materially altered by the inclusion or exclusion of these additional covariates.

6.2 Granger causality

To ensure that our results are properly identified, we address the possibility of endogeneity between regulations and price changes. Specifically, can increases in prior consumer prices lead to an increase in federal regulations? At the local level, examples exist of municipalities enacting ordinances in order to influence prices (e.g., rent control), and most states have public utility commissions that regulate the prices of telephone service and electricity, but there is little evidence that this is occurring at the federal level over the sample period (2000 to 2012). Richard Nixon was responsible for the last imposition of wage and price controls in 1971. Since that time, the trend at the federal level has been toward deregulating interstate service providers and allowing market forces to determine prices (e.g., the elimination of the Interstate Commerce Commission in 1995, which previously regulated rates for rail and truck freight, and the dissolution of the Civil Aeronautics Board in 1985, which had previously regulated interstate airfares). According to RegData, the top ten regulators in 2012 were the: 1) Environmental Protection Agency (EPA), 2) Internal Revenue Service (IRS), 3) Coast Guard, 4) Occupational Safety and Health Administration (OSHA), 5) Federal Communications Commission (FCC), 6) Agricultural Marketing Service (USDA-AMS), 7) Food and Drug Administration (FDA), 8) Federal Aviation Administration (FAA), 9) Department of Defense (DoD), and 10) Federal Energy Regulatory Commission (FERC).[27] Given the missions of the above regulators, one can reasonably conclude that the bulk of the new regulations created by these agencies are related to

[27] Source: RegData (http://regdata.org/how-the-top-ten-regulators-of-2012-changed-over-ten-years/).

environmental quality, taxes/accounting standards, maritime safety/commerce, workplace safety, broadcast/communication rules, food, drug, and medical device safety, aviation safety, the military, and electric power generation. Nonetheless, we conduct a Granger causality test under the null hypothesis that higher consumer prices *do not* Granger-cause new regulations. The test fails to reject the null at any standard level of significance, verifying that prior price increases do not Granger-cause subsequent regulations.[28]

6.3 Cross-section FGLS estimation results

Given that household income groups consume the same goods and services (albeit with differing budget shares), price shocks to any expenditure category will have similar, contemporaneous effects on household-specific price increases. As such, contemporaneous correlation exists in the errors across household groups (i.e., $E(u_t^i u_t^j) \neq 0$ for all $i, j \in h$). Combining this with the fact that the time dimension of our sample exceeds that of the cross-sectional observations (T > N), we can improve the estimation efficiency of Equation (5) using a cross-sectional Feasible Generalized Least Squares (FGLS) weighting matrix similar to that suggested in Zellner (1962). To obtain the weighting matrix, we first estimate equation-by-equation OLS specifications of Equation (5), deriving separate (and consistent) Phillips curve estimates for each household.[29] The residuals from each equation ($\hat{u}^i$) are then stacked to form an $N \times T$ matrix $\hat{u} \equiv$

[28] The unrestricted model is similar to Equation (5), wherein the current growth rate of regulations is regressed on a constant, a lag of itself, current and one-period lags of both unemployment and the GDP gap, and one- and two-period lags of the inflation rate. The restricted model sets the coefficients on the lagged inflation terms equal to zero. The resulting F-stat equals 0.077, which is not significant at any standard level of significance.

[29] As noted by Nickell (1981), all dynamic models with relatively short time dimensions, including autoregressive time series and dynamic panel models, suffer from "Hurwicz type bias," regardless of the estimation procedure used. That said, our estimation procedure is biased but consistent.

$(\hat{u}^1, \hat{u}^2, \dots, \hat{u}^h)'$, which in turn is used to construct an $N{\times}N$, contemporaneous cross-household variance-covariance matrix:

$$\hat{\Sigma} = \frac{1}{T}\hat{u}\hat{u}' = \begin{pmatrix} \hat{\sigma}_{11} & \hat{\sigma}_{12} \cdots & \hat{\sigma}_{1N} \\ \hat{\sigma}_{21} & \ddots & \vdots \\ \vdots & & \\ \hat{\sigma}_{N1} & \cdots & \hat{\sigma}_{NN} \end{pmatrix}.$$

The corresponding $NT{\times}NT$ variance-covariance for the panel residuals thus is

$$\hat{\Omega} = \hat{\Sigma} \otimes I_T = \begin{pmatrix} \hat{\sigma}_{11}I_T & \hat{\sigma}_{12}I_T \cdots & \hat{\sigma}_{1N}I_T \\ \hat{\sigma}_{21}I_T & \ddots & \vdots \\ \vdots & & \\ \hat{\sigma}_{N1}I_T & \cdots & \hat{\sigma}_{NN}I_T \end{pmatrix}.$$

Because most dynamic panels in the literature are assumed to have large N and small T, elimination of the fixed effect by within-transformation (i.e., demeaning each cross-section to remove the invariant fixed effect parameter) is very desirable as it reduces greatly the number of parameters (by N-1). However, as shown by Nickell (1981), doing this in a dynamic panel leads to inconsistent OLS estimates holding T fixed and increasing $N \rightarrow \infty$. Alternatively, one can first difference dynamic panel equations to eliminate the invariant nuisance parameters (fixed effects), but this creates a first-order moving average process in the residuals that is correlated with the first difference of the lagged dependent variable. To overcome this endogeneity, researchers perform GMM estimation using instrumental variables consisting of lagged endogenous variables (see, among others, Anderson and Hsiao 1982; Arellano and Bond 1991). In our model, the cross-sectional dimension is fixed at five (i.e., the household-income quintiles), but the time dimension spans a decade and will continue to grow with new data. Hence, the appropriate test of consistency is fixed N and large T$\rightarrow \infty$. In this framework, Equation (5) can be estimated consistently as a fixed effects model wherein dummy variables are entered to capture household-income quintiles, resulting in only a small loss of degrees of freedom.

Efficiency is improved by employing the FGLS weighting matrix ($\widehat{\Omega}^{-1}$) introduced above. Estimates of Equation (5) following this procedure are reported in Table 6 (columns 3 to 6).

For the sake of comparison, column (3) excludes all control variables except lagged price increases and regulatory growth. The results are very similar to the GMM results reported in column (1). The coefficient on lagged regulatory growth is approximately halved (0.0282), but remains positive and statistically significant. The coefficient on lagged price growth declines slightly in magnitude from -0.4857 to -0.3585.

Columns (4) to (6) of Table 6 report the estimation results for variations of Equation (5), with fixed effects omitted in column (5), and FGLS weighting foregone in column (6). From these results spring three conclusions. First, the estimation results are robust to the estimation methodology, as the cross-sectional FGLS and GMM results are nearly identical (especially when comparing columns (2) and (6)). Second, FGLS weighting reduces the magnitude of the regulation coefficient (compared to column (6), column (4) is 21% smaller and column (5) declines by 27%). Finally, the inclusion or omission of the fixed effects do not systematically affect the coefficient on regulations (comparing columns (4) and (5)). The overall average coefficient on lagged regulations reported in Table 6 equals 0.0890, while the median equals 0.0938. This strongly suggests that a 10% increase in regulations increases consumer prices by just under 1% (i.e., between 0.890% and 0.938%).

6.3 Robustness: Growth dynamics of the underlying goods and services

Our results strongly support the assertion that regulatory restrictions promote higher prices across the socioeconomic spectrum, as measured by changes in the cost of baskets of goods and services purchased by various income groups. To ensure that this result is not driven by the basket weights themselves, we eliminate them completely and investigate the relationship between regulatory growth and price changes for each expenditure category (e.g., bakery products, major appliances, men's apparel). Specifically, we estimate the following dynamic panel model, which does not employ *any* household expenditure weights:

$$p_{it} = \alpha_i + \beta reg_{it-1} + \rho p_{it-1} + u_{it}, \tag{6}$$

where p_{it} is the log first difference of the original price series for expenditure category i ($i = 1, \ldots, 61$), α_i is the unique intercept for each expenditure category, reg_{it-1} is the log first difference of the regulations that apply to expenditure category i in the prior year, and u_{it} is a mean zero error term.[30] Essentially, Equations (5) and (6) are very similar except that we are modeling the price increases for individual expenditure categories rather than the broader rate of inflation over a basket of goods, and we are excluding the aggregate macroeconomic control variables (i.e., the unemployment rate and the output gap). The unique intercepts accommodate different long-run rates of price growth by category type. Because the number of expenditure categories (N=61) exceeds the time dimension (T=10), we use the Arellano and Bond (1991) GMM estimator. The results are reported in Table 7. While smaller in magnitude, the coefficient on lagged regulatory growth is statistically significant, equaling 0.0360. Although statistically significant, the inclusion of a 2008 Great Recession dummy variable makes almost no difference in the coefficient estimate on regulatory growth (see column 2), increasing it to 0.0369. These results imply that a 10% increase in total category-specific regulatory restrictions increases the price of goods and services in that category by an additional 0.36%.

[Table 7 here]

[30] See Table 3 for a list of the detailed expenditure categories.

7. Conclusion

A significant and often hidden cost of regulation is its effect on consumer prices. As with taxes, the burden of regulatory costs is likely to be passed along, at least in part, to consumers in the form of higher prices. While the literature explores other specific costs of regulation, noting that higher consumer prices are a probable consequence of heavy regulation, this study is the first to provide a thorough empirical analysis of that relationship across industries. Our dataset, which combines information from the Consumer Expenditure Survey, RegData, and price changes from the Consumer Price Index, allows us to determine the effects of regulations on prices and to ask whether those effects are regressive.

We document consumer spending patterns by income group and find that the lowest-income households spend a larger fraction of their income in areas that are more heavily regulated. The opposite is true of the wealthiest households: they allocate more of their spending to goods and services that are subject to fewer regulations. Our estimates of the effect of regulatory growth on price levels suggest a positive, robust, and statistically significant relationship. A 10% increase in regulations is associated with just under a 1% increase in prices. This effect is particularly concerning for low-income households, which face larger regulatory-induced price increases than high-income households.

It is important to emphasize that these results do not include state or municipal regulations. If state and local regulations have qualitatively similar impacts on consumer prices, the regressive regulatory impact of all regulations on poor households is even greater than what our results suggest.

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We thank Fabrizio Iacone, Diana Thomas and the participants of the Regressive Effects of Regulation conference at Creighton University for their helpful review and comments. Dustin Chambers and Courtney Collins also thank the Mercatus Center (at George Mason University) for their financial support in drafting an earlier Mercatus Working Paper (February 2016) which motivated the current paper.

Appendix A. Proofs of predictions from theoretical model

Proof of Prediction 1

Consumer i's spending on the regulated commodity as a share of her income is:

$$S_i = \frac{px_i(p,m_i)}{m_i} \tag{A1}$$

Therefore:

$$\ln(S_i) = \ln(p) + \ln(x_i(p,m_i)) - \ln(m_i) \tag{A2}$$

$$\frac{\partial \ln(S_i)}{\partial m_i} = \frac{1}{x_i}\frac{\partial x_i(p,m_i)}{\partial m_i} - \frac{1}{m_i} = \frac{1}{m_i}\left[\varepsilon_m - 1\right] \tag{A3}$$

where ε_m is the income elasticity of demand. Therefore, if demand with respect to income is inelastic, i.e., $0 < \varepsilon_m < 1$, then $\partial \ln(S_i) / \partial m_i < 0$. ■

Proof of Prediction 2

Application of the Implicit Function Theorem to equation (1) yields:

$$\frac{\partial p}{\partial R} = \frac{\frac{\partial x(p,R)}{\partial R}}{\sum_i \frac{\partial x_i(p,m_i)}{\partial p} - \frac{\partial x(p,R)}{\partial p}} > 0 \tag{A4}$$

which shows that p is increasing in R. ■

Proof of Prediction 3

Consumer i's budget constraint is:

$$px_i(p,m_i) + y_i = m_i \tag{A5}$$

where y_i denotes consumer i's expenditure on all commodities other than x_i. Dividing the budget constraint by m_i yields:

$$\frac{px_i(p,m_i)}{m_i} + \frac{y_i}{m_i} = 1 \tag{A6}$$

and differentiating with respect to R yields:

$$\frac{x_i}{m_i}\frac{\partial p}{\partial R}+\frac{p}{m_i}\frac{\partial x_i(p,m_i)}{\partial p}\frac{\partial p}{\partial R}+\frac{1}{m_i}\frac{\partial y_i}{\partial p}\frac{\partial p}{\partial R}=0 \tag{A7}$$

Recall that $\partial p/\partial R>0$ (Prediction 2). Equation (A7) can be simplified to:

$$\frac{1}{m_i}\frac{\partial y_i}{\partial p}=\frac{-x_i}{m_i}\left[1+\varepsilon_p\right] \tag{A8}$$

where ε_p is the regulated commodity's price elasticity of demand. The left-hand side of equation (A8) shows the proportional change in consumer i's spending on other commodities when p increases. Recall that x_i/m_i is decreasing in m_i if demand with respect to income is inelastic (Prediction 1). Therefore, if demand with respect to price is also inelastic, i.e., $-1<\varepsilon_p<0$, then an increase in p causes lower-income consumers to reduce their spending on other commodities by proportionately more than it does for higher-income consumers. ■

Appendix B. Methodological description of the construction of the consumer expenditure survey and regulation datasets

To determine the disparate effects of government regulations on households in different socioeconomic strata, we construct a dataset that maps goods and services from the Consumer Expenditure Survey (CE) onto industry regulations from the Mercatus Center at George Mason University's industry regulation database (RegData).

The CE provides detailed household spending and price data for a wide array of goods and services by income group. These goods and services are organized using the Universal Classification Codes (UCC) system. RegData 2.0, however, reports the level of industry regulation by the two-, three-, and four-digit North American Industry Classification System (NAICS) code for each year between 1997 and 2012. Therefore, to construct a usable database, we map regulations from the NAICS space onto goods and services in the UCC space. The resulting balanced panel dataset contains 9,872 observations, covering 617 UCC-based goods and services over a 16-year period.

To construct the final dataset, the following steps are employed:

1. The RegData 2.0 dataset consists of two-digit, three-digit, and four-digit NAICS-based tables. Each regulation record in the tables contains the name of the government agency imposing the regulation, the year of the regulation, the industry affected by the regulation, the regulatory word count, the restriction count, and the industry regulation index value. For our purposes, we use the industry regulation index value, which equals the regulatory restriction count weighted by industry relevance.[31]

[31] For a description of the methodology used to construct RegData, see http://regdata.org/methodology.

For each industry-and-year pair, the industry regulation index values are summed across federal regulators. Therefore, for each industry-and-year combination, a single-industry regulation index value is derived, equaling the sum of all regulatory restrictions (weighted by industry relevance) imposed on that industry by all federal regulators for that year. The result is three aggregated datasets, one for each two-digit, three-digit, and four-digit NAICS-based table. Last, the three aggregated datasets are combined (stacked) to form a single dataset.

2. The spreadsheet containing the 2007 commodity-by-industry direct requirements (after redefinitions) table was downloaded from the Bureau of Economic Analysis (BEA) website (http://www.bea.gov/industry/xls/io-annual/CxI_DR_2007_detail.xlsx). This spreadsheet contains two work sheets, both of which are used below:
    a. The first work sheet is a concordance that converts the BEA's input-output (I-O) commodity/industry codes into 2007 NAICS codes.
    b. The second work sheet is the I-O direct requirements table, which contains I-O weights (α_{ij}) equal to the amount of input (measured in dollars) from industry (i) required to produce a dollar's worth of output by industry (j). By construction, these weights sum to 1 because, in addition to actual inputs, the BEA includes employee compensation, taxes, and gross operating surplus in the weighting schema.
3. The I-O commodity/industry code to NAICS concordance described in step (2a) above is matched with the aggregate industry regulations from step (1), to create a new table that lists the aggregate industry regulations by I-O commodity/industry code; the resulting table is further summed over commodity code by year to derive a table with a

single total regulation value for each commodity code–year pair. This second round of aggregation after the initial match is necessary because some commodity codes map onto multiple NAICS industries. I-O commodity/industry codes with no associated regulations are assigned an industry regulation index value of 0. The resulting table is a measure of the direct regulations (denoted $DirectReg_{it}$) applicable to a given I-O commodity/industry code.

4. To determine the level of regulation that applies to the inputs/supply chain of a given industry, the I-O direct requirements (α_{ij}) from step (2b) are matched with the direct regulations for each I-O commodity ($DirectReg_{it}$) from step (3) by way of their I-O commodity/industry codes. Note that if a commodity/industry is not needed to produce a given output, the associated input value is 0. This produces a large result set with more than 2.4 million rows of data. This dataset is then "grouped by" output industry (j) and year (t) and summed over the product of the direct input regulations (indexed by i) and I-O weights, producing an estimate of input–supply chain regulation:

$$InputReg_{jt} = \sum_i \alpha_{ij} \cdot DirectReg_{it}.$$

See Figure B1 for a graphical summary of steps (1) to (4).

[Figure B1 here]

5. The direct regulations by industry and year are matched with the total input regulations by industry and year. The direct and input regulations are summed to determine the total direct and indirect regulations affecting a given industry:

$$TotalReg_{it} = DirectReg_{it} + InputReg_{it}.$$

6. To map regulations onto the UCC codes, a separate set of queries is executed to map the codes onto I-O commodity/industry codes.
   a. As a beginning step, we import the personal consumption expenditures (PCE) concordance from the Bureau of Labor Statistics (BLS) (http://www.bls.gov/cex /pce_concordance_2012.xlsx). This file maps UCC codes onto PCE codes from the BEA's national income and product accounts (NIPAs).
   b. Next, we import BEA table 2.4.5U (I-O, Personal Consumption Expenditures by Type of Product with 2007 Input-Output Commodity Composition). This latter bridge file (http://www.bea.gov/national/xls/2007-pcs-io-bridge.xls) maps NIPA line numbers onto PCE codes.
   c. The tables from steps (6a) and (6b) are matched by way of their common PCE codes. The resulting table serves as a bridge file that maps UCC codes onto NIPA line numbers.
7. Finally, we import the BEA's PCE bridge file, which maps NIPA line numbers onto I-O commodity/industry codes (www.bea.gov/industry/xls/io-annual/PCEBridge_2007 _Detail.xlsx), along with the total value of all purchases of the linked I-O commodity/industry in 2007.
   a. Matching the NIPA line items from the PCE bridge with the results from step (6c) provides a clear mapping from UCC code to I-O commodity/industry codes. See Figure B2 for a graphic summary of steps (6) and (7).

[Figure B2 here]

8. The resulting table from step (7a) maps a given consumer product from the CE onto all I-O industries that produce that product. In many cases, more than one industry produces a given UCC product. To produce a single regulation value for each consumer product, we derive industry weights equal to a given industry's 2007 level of output relative to the total output of all industries that supply a given UCC product.[32] For example, the UCC code for flour is 10110. This consumer product is produced by seven I-O industries. Assigning each of these industries a weight equal to its total output relative to the total output of all seven industries produces a set of weights that sum to 1 (see table B1). Although it would be preferable to update these weights annually, the BLS derives these output data from the US Census Bureau's Economic Census, which is conducted only every five years.

[Table B1 here]

9. Finally, UCC codes, I-O commodity/industry codes, and output shares from step (8) are matched with the regulation-by-industry data from step (5). These matched data are then "grouped by" UCC code and year and aggregated over the product of industry regulation and output shares.

[32] Consumption-based weights equal to each industry's market share for a given commodity would be preferable to weights based on the overall relative size of the industries that produce said commodity. Unfortunately, to our knowledge, no such data exist.

Appendix C. Top 20 expenditure categories by income quintile and corresponding regulations

Income Quintile 1 (Bottom 20%)

Expenditure Category	Expenditure	Direct Reg Rank	Direct Regs	Total Reg Rank	Total Regs
Rented dwellings	14.67%	15	14,741	25	26,084
Owned dwellings	8.55%	7	84,121	8	135,787
Medical services and insurance	5.80%	4	166,222	7	262,865
Food away from home	5.47%	37	473	45	16,430
Gasoline and motor oil	4.66%	5	161,726	3	428,323
Electricity	4.19%	26	1,725	9	92,603
Cars and trucks, used	3.55%	55	0	61	0
Telephone services	3.25%	9	33,094	14	47,054
Education	3.12%	24	1,917	52	14,599
Audio and visual equipment and services	2.37%	22	3,877	58	13,272
Vehicle insurance	2.23%	2	306,785	1	477,185
Drugs and medical supplies	2.07%	33	826	44	16,580
Cars and trucks, new	2.05%	44	101	60	6,412
Miscellaneous foods	1.86%	53	2	31	20,640
Miscellaneous	1.80%	8	34,464	11	54,266
Household operations	1.67%	46	70	59	6,613
Housekeeping supplies	1.64%	20	9,331	20	32,149
Maintenance and repairs	1.62%	16	13,006	26	24,941
Small appliances, misc. housewares, and household equip.	1.58%	36	593	37	17,557
Women's apparel, age 16 and over	1.51%	30	1,236	43	17,276

Income Quintile 2

Expenditure Category	Expenditure	Direct Reg Rank	Direct Regs	Total Reg Rank	Total Regs
Rented dwellings	11.38%	15	14,741	25	26,084
Owned dwellings	10.24%	7	84,121	8	135,787
Medical services and insurance	6.60%	4	166,222	7	262,865
Food away from home	5.61%	37	473	45	16,430
Gasoline and motor oil	5.33%	5	161,726	3	428,323
Cars and trucks, used	4.47%	55	0	61	0
Electricity	3.86%	26	1,725	9	92,603
Telephone services	3.18%	9	33,094	14	47,054
Cars and trucks, new	2.72%	44	101	60	6,412
Vehicle insurance	2.65%	2	306,785	1	477,185
Audio and visual equipment and services	2.34%	22	3,877	58	13,272
Drugs and medical supplies	2.18%	33	826	44	16,580
Miscellaneous	1.99%	8	34,464	11	54,266
Maintenance and repairs	1.84%	16	13,006	26	24,941
Household operations	1.81%	46	70	59	6,613
Small appliances, misc. housewares, and household equip.	1.72%	36	593	37	17,557
Miscellaneous foods	1.68%	53	2	31	20,640
Housekeeping supplies	1.63%	20	9,331	20	32,149
Personal care products and services	1.48%	35	613	57	13,342
Women's apparel, age 16 and over	1.37%	30	1,236	43	17,276

Income Quintile 3

Expenditure Category	Expenditure	Direct Reg Rank	Direct Regs	Total Reg Rank	Total Regs
Owned dwellings	12.75%	7	84,121	8	135,787
Rented dwellings	8.47%	15	14,741	25	26,084
Food away from home	6.20%	37	473	45	16,430
Medical services and insurance	6.09%	4	166,222	7	262,865
Gasoline and motor oil	5.58%	5	161,726	3	428,323
Cars and trucks, used	4.59%	55	0	61	0
Cars and trucks, new	3.64%	44	101	60	6,412
Electricity	3.39%	26	1,725	9	92,603
Telephone services	3.04%	9	33,094	14	47,054
Vehicle insurance	2.75%	2	306,785	1	477,185
Audio and visual equipment and services	2.31%	22	3,877	58	13,272
Miscellaneous	2.04%	8	34,464	11	54,266
Small appliances, misc. housewares, and household equip.	1.95%	36	593	37	17,557
Maintenance and repairs	1.90%	16	13,006	26	24,941
Household operations	1.81%	46	70	59	6,613
Drugs and medical supplies	1.71%	33	826	44	16,580
Miscellaneous foods	1.60%	53	2	31	20,640
Housekeeping supplies	1.51%	20	9,331	20	32,149
Personal care products and services	1.45%	35	613	57	13,342
Women's apparel, age 16 and over	1.43%	30	1,236	43	17,276

Income Quintile 4

Expenditure Category	Expenditure	Direct Reg Rank	Direct Regs	Total Reg Rank	Total Regs
Owned dwellings	15.50%	7	84,121	8	135,787
Food away from home	6.70%	37	473	45	16,430
Medical services and insurance	5.52%	4	166,222	7	262,865
Gasoline and motor oil	5.29%	5	161,726	3	428,323
Rented dwellings	4.99%	15	14,741	25	26,084
Cars and trucks, used	4.59%	55	0	61	0
Cars and trucks, new	4.41%	44	101	60	6,412
Electricity	2.88%	26	1,725	9	92,603
Telephone services	2.74%	9	33,094	14	47,054
Vehicle insurance	2.61%	2	306,785	1	477,185
Audio and visual equipment and services	2.22%	22	3,877	58	13,272
Small appliances, misc. housewares, and household equip.	2.15%	36	593	37	17,557
Household operations	2.06%	46	70	59	6,613
Miscellaneous	2.04%	8	34,464	11	54,266
Maintenance and repairs	1.90%	16	13,006	26	24,941
Education	1.71%	24	1,917	52	14,599
Housekeeping supplies	1.61%	20	9,331	20	32,149
Miscellaneous foods	1.54%	53	2	31	20,640
Women's apparel, age 16 and over	1.51%	30	1,236	43	17,276
Personal care products and services	1.47%	35	613	57	13,342

Income Quintile 5					
Expenditure Category	Expenditure	Direct Reg Rank	Direct Regs	Total Reg Rank	Total Regs
Owned dwellings	18.55%	7	84,121	8	135,787
Food away from home	6.90%	37	473	45	16,430
Cars and trucks, new	5.29%	44	101	60	6,412
Medical services and insurance	4.60%	4	166,222	7	262,865
Gasoline and motor oil	4.21%	5	161,726	3	428,323
Cars and trucks, used	3.33%	55	0	61	0
Education	3.30%	24	1,917	52	14,599
Household operations	2.91%	46	70	59	6,613
Small appliances, misc. housewares, and household equip.	2.48%	36	593	37	17,557
Electricity	2.27%	26	1,725	9	92,603
Other lodging	2.27%	21	5,352	24	26,406
Rented dwellings	2.17%	15	14,741	25	26,084
Fees and admissions	2.15%	55	0	21	29,019
Telephone services	2.14%	9	33,094	14	47,054
Vehicle insurance	2.11%	2	306,785	1	477,185
Miscellaneous	2.05%	8	34,464	11	54,266
Audio and visual equipment and services	1.95%	22	3,877	58	13,272
Maintenance and repairs	1.79%	16	13,006	26	24,941
Women’s apparel, age 16 and over	1.66%	30	1,236	43	17,276
Public transportation	1.64%	1	382,599	2	435,932

Note: Regulations are measured by way of industry regulation index value; see Appendix B for details.

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Table 1. Average percentage of total expenditure on regulated categories by income quintiles from 2000–2012

	Bottom 20%	Quintile 2	Quintile 3	Quintile 4	Top 20%	% Difference (Bottom vs. Top Quintile)
25 Most-Regulated Expenditure Categories						
Direct Regulations	60.15%	58.42%	57.22%	57.22%	54.51%	10.35%
Total Regulations	58.73%	58.13%	56.64%	54.31%	52.23%	12.44%
25 Least-Regulated Expenditure Categories						
Direct Regulations	25.64%	27.28%	28.99%	30.97%	32.19%	-20.35%
Total Regulations	31.88%	32.22%	33.92%	36.07%	38.63%	-17.47%

Table 2. Expenditure categories with largest differences in spending between bottom and top income quintiles, 2000–2012

Expenditure Category	Bottom Quintile	Top Quintile	Difference	% Difference
Rented dwellings	14.67%	2.17%	12.50%	576.04%
Electricity	4.19%	2.27%	1.92%	84.58%
Medical services and insurance	5.80%	4.60%	1.20%	26.09%
Telephone services	3.25%	2.14%	1.11%	51.87%
Tobacco products and smoking supplies	1.41%	0.41%	1.00%	243.90%
Drugs and medical supplies	2.07%	1.13%	0.94%	83.19%
Miscellaneous foods	1.86%	1.26%	0.60%	47.62%
Gasoline and motor oil	4.66%	4.21%	0.45%	10.69%
Nonalcoholic beverages	1.04%	0.62%	0.42%	67.74%
Audio and visual equipment and services	2.37%	1.95%	0.42%	21.54%

Note: Values represent the percentage of expenditures each income quintile allocates to specific expenditure categories.

Table 3. Average basket shares and regulations by income quintile

Expenditure Category	Average Basket Weights (2000 to 2012)					Average Regulations		
	Bottom 20%	2nd Quintile	3rd Quintile	4th Quintile	Top 20%	Direct	Input	Total
Alcoholic beverages	0.98%	0.96%	1.06%	1.13%	1.20%	1,000	18,139	19,140
Audio and visual equipment and services	2.37%	2.34%	2.31%	2.22%	1.95%	3,877	9,396	13,272
Bakery products	1.05%	0.96%	0.87%	0.81%	0.67%	411	15,695	16,106
Beef	0.76%	0.74%	0.65%	0.59%	0.48%	11,219	30,471	41,691
Boys' apparel, ages 2 to 15	0.23%	0.23%	0.23%	0.23%	0.24%	1,255	16,200	17,456
Cars and trucks, new	2.05%	2.72%	3.64%	4.41%	5.29%	101	6,311	6,412
Cars and trucks, used	3.55%	4.47%	4.59%	4.59%	3.33%	0	0	0
Cereals and cereal products	0.56%	0.49%	0.44%	0.39%	0.33%	180	22,418	22,597
Children's apparel, under age 2	0.26%	0.24%	0.23%	0.23%	0.18%	620	14,451	15,071
Drugs and medical supplies	2.07%	2.18%	1.71%	1.40%	1.13%	826	15,754	16,580
Education	3.12%	1.29%	1.31%	1.71%	3.30%	1,917	12,682	14,599
Eggs	0.18%	0.11%	0.11%	0.12%	0.10%	21,764	25,261	47,025
Electricity	4.19%	3.86%	3.39%	2.88%	2.27%	1,725	90,877	92,603
Fats and oils	0.34%	0.31%	0.24%	0.23%	0.16%	8	21,970	21,978
Fees and admissions	0.79%	0.81%	1.04%	1.35%	2.15%	0	29,019	29,019
Fish and seafood	0.38%	0.35%	0.31%	0.29%	0.25%	235,349	147,703	383,052
Floor coverings	0.06%	0.08%	0.09%	0.10%	0.14%	0	14,270	14,270
Food away from home	5.47%	5.61%	6.20%	6.70%	6.90%	473	15,957	16,430
Food prepared by consumer unit on out-of-town trips	0.10%	0.11%	0.11%	0.12%	0.12%	473	15,957	16,430
Footwear	0.99%	0.88%	0.84%	0.79%	0.76%	1,790	25,395	27,184
Fresh fruits	0.64%	0.60%	0.53%	0.49%	0.43%	2	17,568	17,569
Fresh milk and cream	0.53%	0.48%	0.40%	0.35%	0.25%	24	27,026	27,050
Fresh vegetables	0.62%	0.59%	0.51%	0.47%	0.41%	1	14,492	14,493
Fuel oil and other fuels	0.41%	0.39%	0.33%	0.32%	0.28%	116,284	251,824	368,108
Furniture	0.72%	0.75%	0.85%	0.95%	1.35%	17	17,310	17,327
Gasoline and motor oil	4.66%	5.33%	5.58%	5.29%	4.21%	161,726	266,598	428,323
Girls' apparel, ages 2 to 15	0.25%	0.29%	0.30%	0.31%	0.33%	1,236	16,040	17,276
Household operations	1.67%	1.81%	1.81%	2.06%	2.91%	70	6,543	6,613
Household textiles	0.25%	0.30%	0.32%	0.33%	0.37%	71	15,403	15,475
Housekeeping supplies	1.64%	1.63%	1.51%	1.61%	1.42%	9,331	22,819	32,149
Maintenance and repairs	1.62%	1.84%	1.90%	1.90%	1.79%	13,006	11,935	24,941
Major appliances	0.42%	0.47%	0.51%	0.55%	0.59%	217	13,578	13,796

Table 3. Continued

	Average Basket Weights (2000 to 2012)					Average Regulations		
Expenditure Category	Bottom 20%	2nd Quintile	3rd Quintile	4th Quintile	Top 20%	Direct	Input	Total
Medical services and insurance	5.80%	6.60%	6.09%	5.52%	4.60%	166,222	96,644	262,865
Men's apparel, age 16 and over	0.69%	0.71%	0.78%	0.86%	1.00%	1,255	16,200	17,456
Miscellaneous	1.80%	1.99%	2.04%	2.04%	2.05%	34,464	19,803	54,266
Miscellaneous foods	1.86%	1.68%	1.60%	1.54%	1.26%	2	20,638	20,640
Natural gas	1.30%	1.29%	1.14%	1.03%	0.91%	18,733	259,424	278,157
Nonalcoholic beverages	1.04%	0.95%	0.86%	0.80%	0.62%	0	17,400	17,400
Other apparel products and services	0.59%	0.55%	0.54%	0.54%	0.86%	110	16,175	16,286
Other dairy products	0.69%	0.65%	0.62%	0.59%	0.51%	19	24,429	24,448
Other entertainment supplies, equipment, and services	0.57%	0.81%	0.90%	1.23%	1.44%	3,533	17,021	20,554
Other lodging	0.89%	0.76%	0.89%	1.17%	2.27%	5,352	21,054	26,406
Other meats	0.36%	0.34%	0.31%	0.25%	0.25%	20,967	30,794	51,761
Other vehicles and vehicle finance charges	0.45%	0.71%	1.03%	1.24%	0.99%	0	14,706	14,706
Owned dwellings	8.55%	10.24%	12.75%	15.50%	18.55%	84,121	51,666	135,787
Personal care products and services	1.46%	1.48%	1.45%	1.47%	1.48%	613	12,729	13,342
Pets, toys, hobbies, and playground equipment	0.96%	1.27%	1.25%	1.29%	1.31%	868	19,231	20,099
Pork	0.62%	0.55%	0.48%	0.40%	0.30%	12,844	30,525	43,369
Poultry	0.53%	0.47%	0.40%	0.38%	0.29%	11,219	39,140	50,359
Processed fruits and vegetables	0.73%	0.67%	0.55%	0.51%	0.42%	0	22,501	22,501
Public transportation	0.88%	0.85%	0.92%	1.03%	1.64%	382,599	53,333	435,932
Reading	0.30%	0.29%	0.29%	0.31%	0.33%	432	14,104	14,536
Rented dwellings	14.67%	11.38%	8.47%	4.99%	2.17%	14,741	11,343	26,084
Small appliances, misc. housewares, and household equip.	1.58%	1.72%	1.95%	2.15%	2.48%	593	16,964	17,557
Sugar and other sweets	0.41%	0.38%	0.34%	0.34%	0.27%	21	19,472	19,493
Telephone services	3.25%	3.18%	3.04%	2.74%	2.14%	33,094	13,961	47,054
Tobacco products and smoking supplies	1.41%	1.24%	1.10%	0.83%	0.41%	29,159	6,696	35,854
Vehicle insurance	2.23%	2.65%	2.75%	2.61%	2.11%	306,785	170,400	477,185
Vehicle rentals, leases, licenses, and other charges	0.75%	0.84%	1.01%	1.20%	1.53%	0	34,902	34,902
Water and other public services	1.16%	1.17%	1.09%	1.03%	0.84%	27,845	62,090	89,935
Women's apparel, age 16 and over	1.51%	1.37%	1.43%	1.51%	1.66%	1,236	16,040	17,276

Table 4. Combined household weighted regulations, all households

Year	Direct Regulations	Input Regulations	Total Regulations
2000	42,283	41,608	83,890
2001	43,454	42,697	86,151
2002	42,998	42,661	85,659
2003	43,578	43,651	87,228
2004	45,786	46,266	92,051
2005	44,926	46,868	91,793
2006	46,056	47,990	94,046
2007	47,627	49,188	96,815
2008	50,214	53,343	103,556
2009	47,575	48,833	96,409
2010	50,569	51,759	102,328
2011	52,399	55,618	108,017
2012	54,523	57,570	112,092

Note: Regulations are measured by way of industry regulation index value; see Appendix B for details.

Table 5. Laspeyres and chained price indexes

Laspeyres

Year	All Households	Bottom 20%	2nd Quantile	3rd Quantile	4th Quantile	Top 20%
2000	100.000	100.000	100.000	100.000	100.000	100.000
2001	101.114	101.388	101.216	101.149	100.999	101.117
2002	103.395	103.832	103.568	103.449	103.180	103.234
2003	104.800	105.473	105.125	104.847	104.420	104.523
2004	108.431	109.297	108.923	108.517	108.019	107.828
2005	112.241	113.488	112.967	112.342	111.663	111.272
2006	115.064	116.487	115.776	115.141	114.357	114.032
2007	120.292	122.091	121.307	120.522	119.504	118.740
2008	119.927	122.360	121.272	120.115	118.848	118.631
2009	124.303	126.703	125.765	124.819	123.432	122.479
2010	126.459	129.117	128.177	127.099	125.570	124.288
2011	130.628	133.545	132.644	131.392	129.711	128.136
2012	132.976	135.989	135.048	133.772	132.003	130.391
Inflation Rate	2.40%	2.59%	2.54%	2.45%	2.34%	2.24%

Chained

Year	All Households	Bottom 20%	2nd Quantile	3rd Quantile	4th Quantile	Top 20%
2000	100.000	100.000	100.000	100.000	100.000	100.000
2001	100.937	101.201	101.008	100.880	100.821	100.955
2002	103.225	103.595	103.403	103.186	103.028	103.077
2003	104.479	105.248	104.827	104.350	104.001	104.257
2004	108.019	108.995	108.553	108.063	107.524	107.474
2005	111.638	113.126	112.483	111.865	111.083	110.777
2006	114.326	116.119	115.251	114.560	113.731	113.377
2007	119.122	121.388	120.529	119.649	118.631	117.646
2008	118.218	121.336	119.509	118.279	117.283	117.105
2009	122.411	125.388	124.097	122.958	121.777	120.834
2010	124.121	127.319	126.048	124.829	123.548	122.313
2011	127.872	131.422	130.034	128.741	127.312	125.842
2012	130.085	133.850	132.318	130.983	129.460	127.977
Inflation Rate	2.22%	2.46%	2.36%	2.27%	2.17%	2.08%

Table 6. Inflation and regulation growth regression results

	GMM		Cross-Section FGLS			
Coefficient	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Regulation growth (t-1)	0.0687***	0.1258***	0.0282***	0.0976***	0.0900***	0.1235***
	(0.0148)	(0.0095)	(0.01)	(0.0135)	(0.023)	(0.0193)
Inflation (t-1)	-0.4857***	-0.8097***	-0.3585**	-0.8384***	-0.3110**	-0.8059***
	(0.0397)	(0.035)	(0.1343)	(0.0678)	(0.1292)	(0.0915)
Unemployment (t)		0.0097***		0.0086***	0.0124***	0.0096***
		(0.0013)		(0.0011)	(0.0036)	(0.0015)
Unemployment (t-1)		-0.0093***		-0.0083***	-0.0077**	-0.0092***
		(0.0013)		(0.0011)	(0.0037)	(0.0015)
Output Gap (t)		0.0177***		0.0164***	0.0156***	0.0176***
		(0.0014)		(0.0014)	(0.0042)	(0.0018)
Output Gap (t-1)		-0.0093***		-0.0081***	-0.0025	-0.0092***
		(0.0011)		(0.0013)	(0.0036)	(0.0017)
2008 time dummy		-0.0249***		-0.0234***	-0.0474***	-0.0250***
		(0.0021)		(0.0023)	(0.0087)	(0.0033)
Observations	50	50	55	55	55	55
Sargan test	4.95	35.07	---	---	---	---
Sargan p-value	0.18	0.11	---	---	---	---
Fixed Effects?	---	---	Yes	Yes	No	Yes
FGLS Weighting	---	---	Yes	Yes	Yes	No
Goodness of Fit	---	---	0.643	0.945	0.649	0.955

Note:

Statistical significance at the 10%, 5%, and 1% levels denoted *, **, and *** respectively.

For GMM estimation results, White robust (period) standard errors in parenthesis. GMM instruments consist of predetermined endogenous variables in levels lagged between two and four periods, while the remaining exogenous variables (i.e., regulation growth, unemployment, and the output gap) are first differenced and serve as their own instruments (the one exception being the 2008 period dummy, which enters the instrument set in level). In both columns (1) and (2), Sargan test fails to reject null hypothesis that overidentifying restrictions are valid at any standard level of significance. Sargan test not applicable to Cross-Sectional FGLS results.

For cross-sectional FGLS results, ordinary standard errors are reported (the use of cross-sectional weights renders White robust (period) standard errors inappropriate in this model specification). Models not employing FGLS weighting (i.e., column (6)) report cross-sectional SURE PCSE standard errors.

Table 7. Expenditure category inflation and regulation growth regression results

Coefficient	(1)	(2)
Lagged regulation growth	0.0360***	0.0369***
	(0.0089)	(0.0093)
Lagged inflation	-0.1998***	-0.1969***
	(0.0031)	(0.0027)
2008 time dummy		-0.0088***
		(0.0017)
Observations	610	610
Sargan test	47.36	50.28
Sargan p-value	0.17	0.11

Note: White robust (period) standard errors in parenthesis

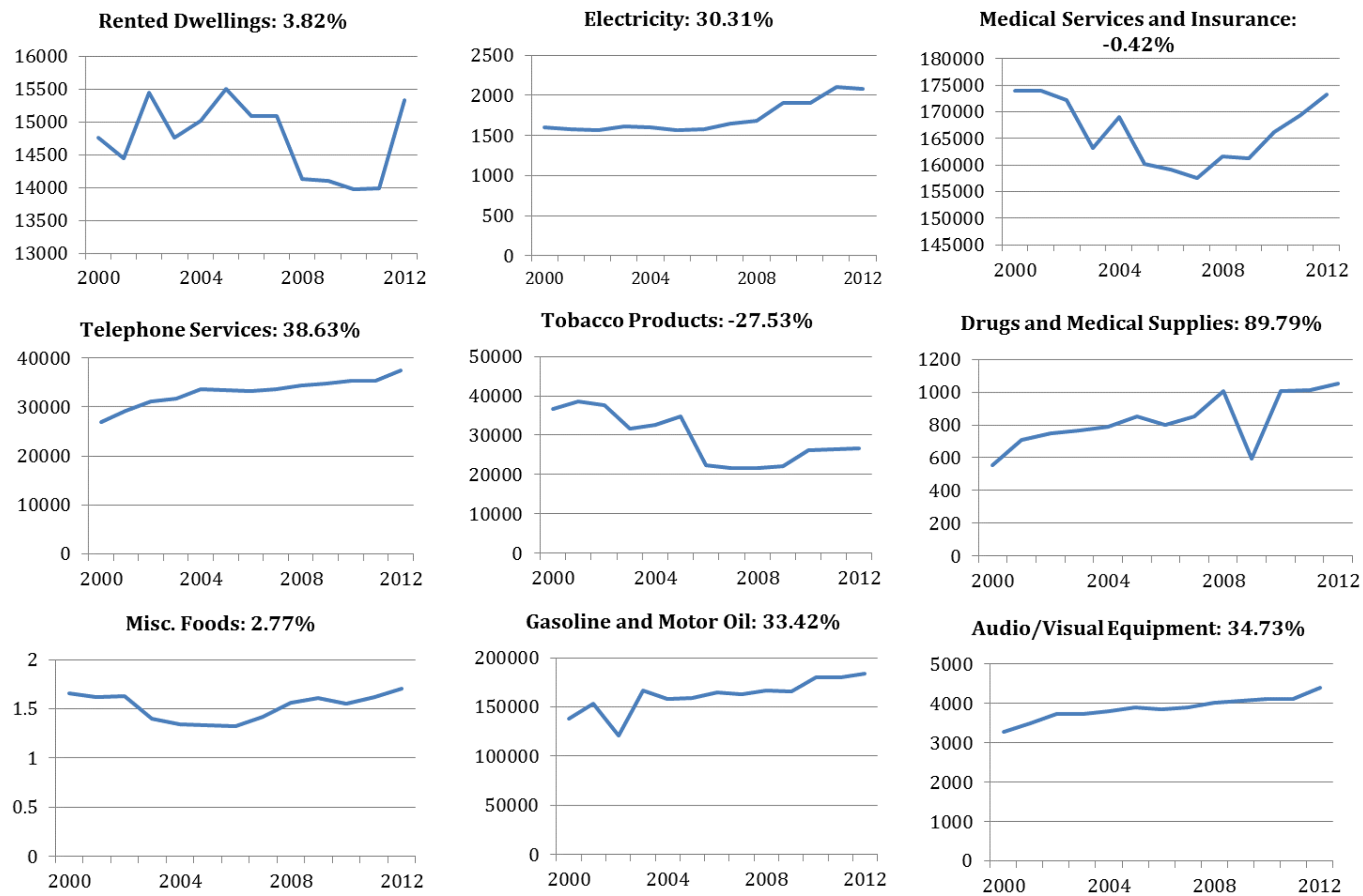
*** denotes 1% significance

Sargan test fails to reject null hypothesis that overidentifying restrictions are valid at any standard level of significance

Table B1. Input-Output industries that produce flour (UCC: 10110)

Commodity Code	Commodity/Industry Description	Purchase Value	Output Share, %
311230	Breakfast cereal manufacturing	12,889	34.7
31122A	Soybean and other oilseed processing	114	0.3
3118A0	Cookie, cracker, pasta, and tortilla manufacturing	16,255	43.8
311210	Flour milling and malt manufacturing	4,659	12.5
311990	All other food manufacturing	660	1.8
1111B0	Grain farming	618	1.7
311420	Fruit and vegetable canning, pickling, and drying	1,939	5.2

Figure 1. Changes in direct regulations across time (2000–2012) for selected expenditure categories



Note: Direct regulations, measured on the y-axes, are measured by way of industry regulation index value; see Appendix B for more details. Numbers after chart titles represent the overall percentage growth from 2000 to 2012.

Figure 2. Total regulations versus chained prices

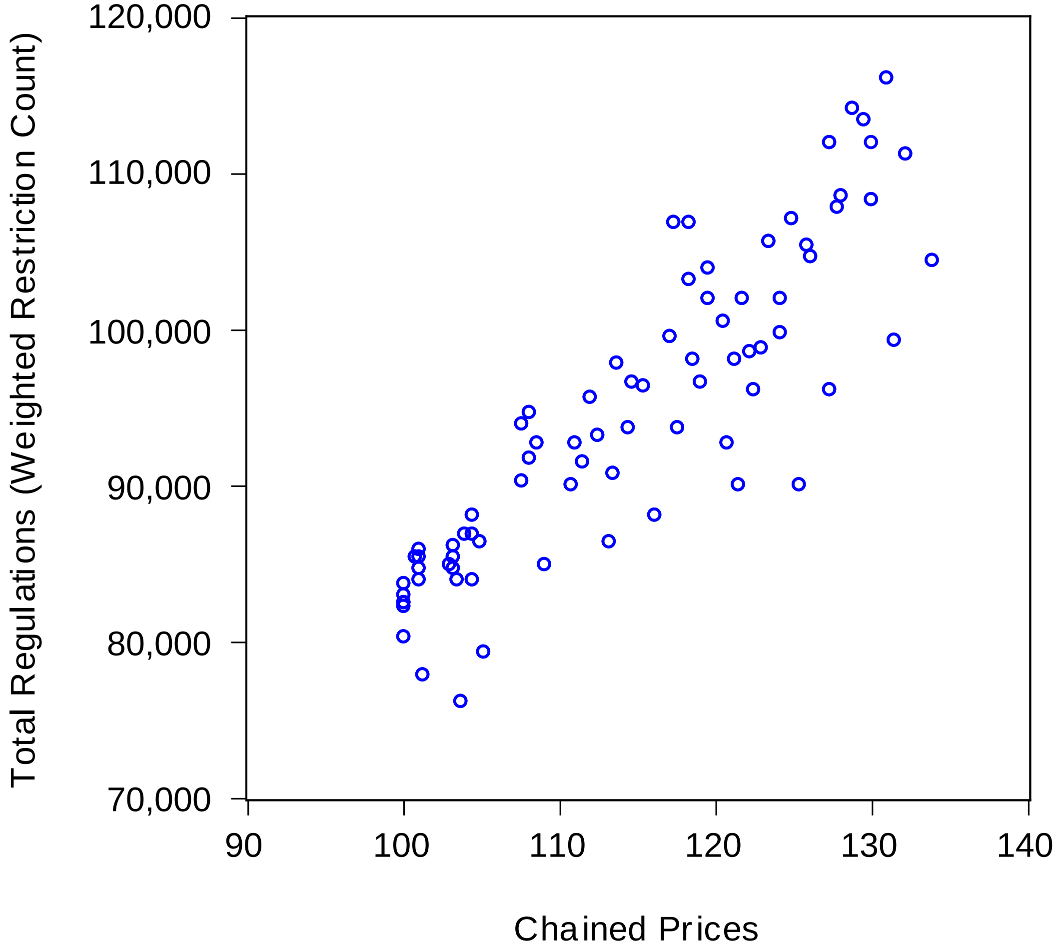


Figure 3. All-household average rate of inflation

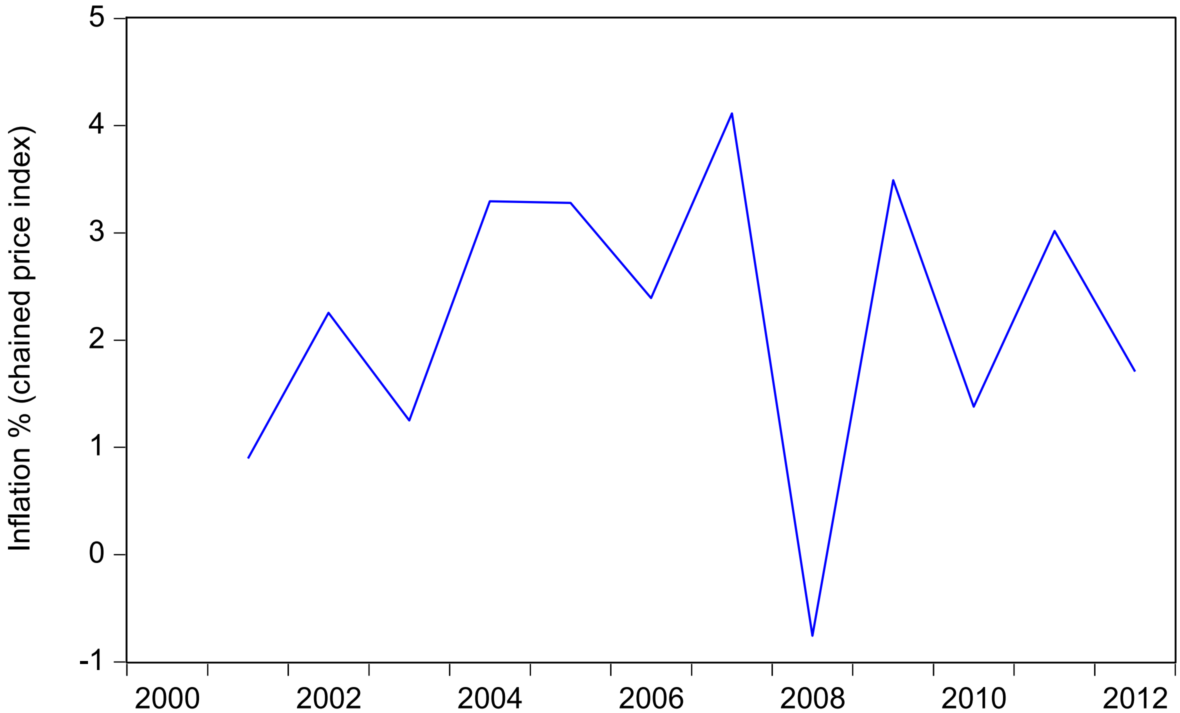
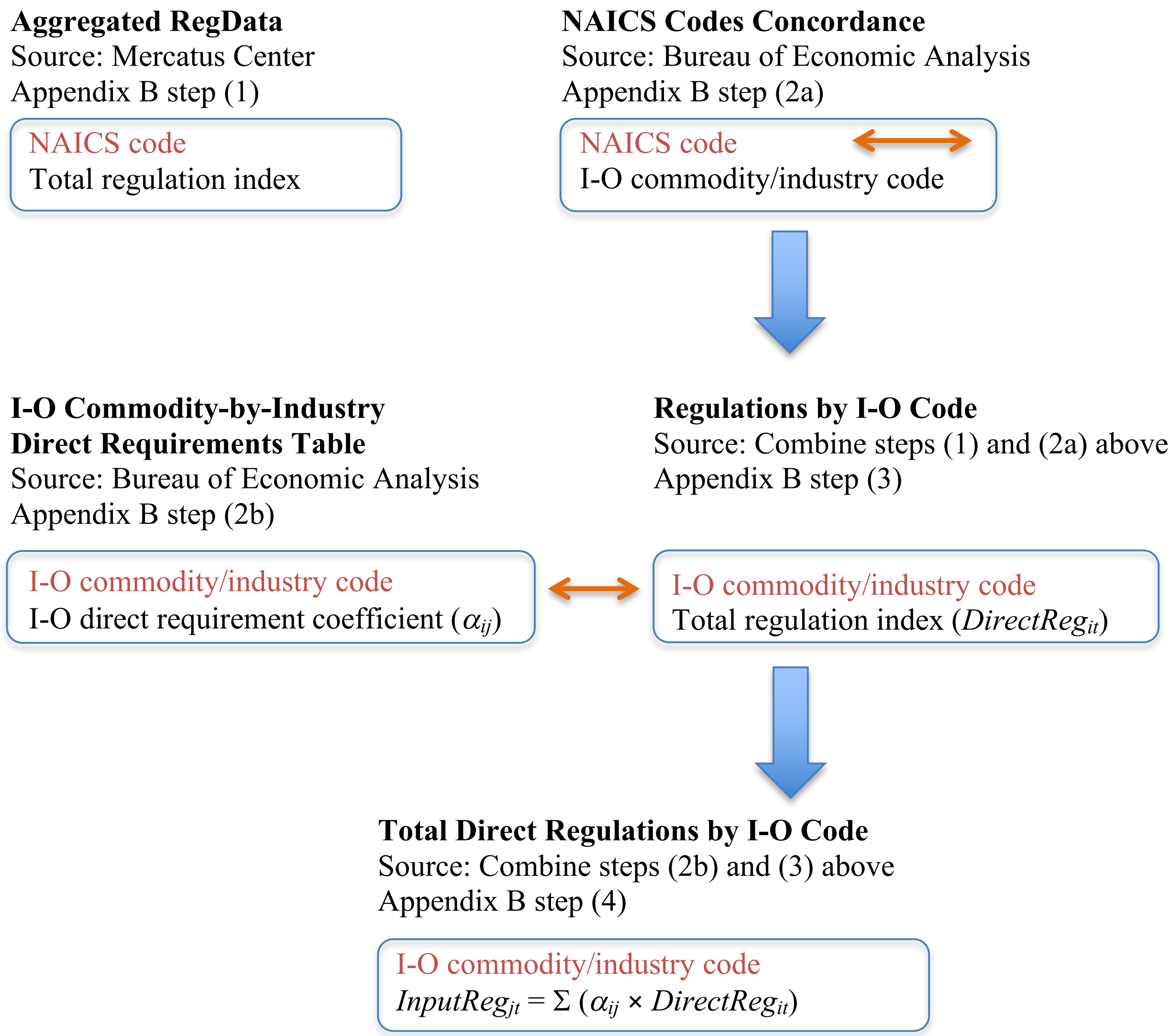
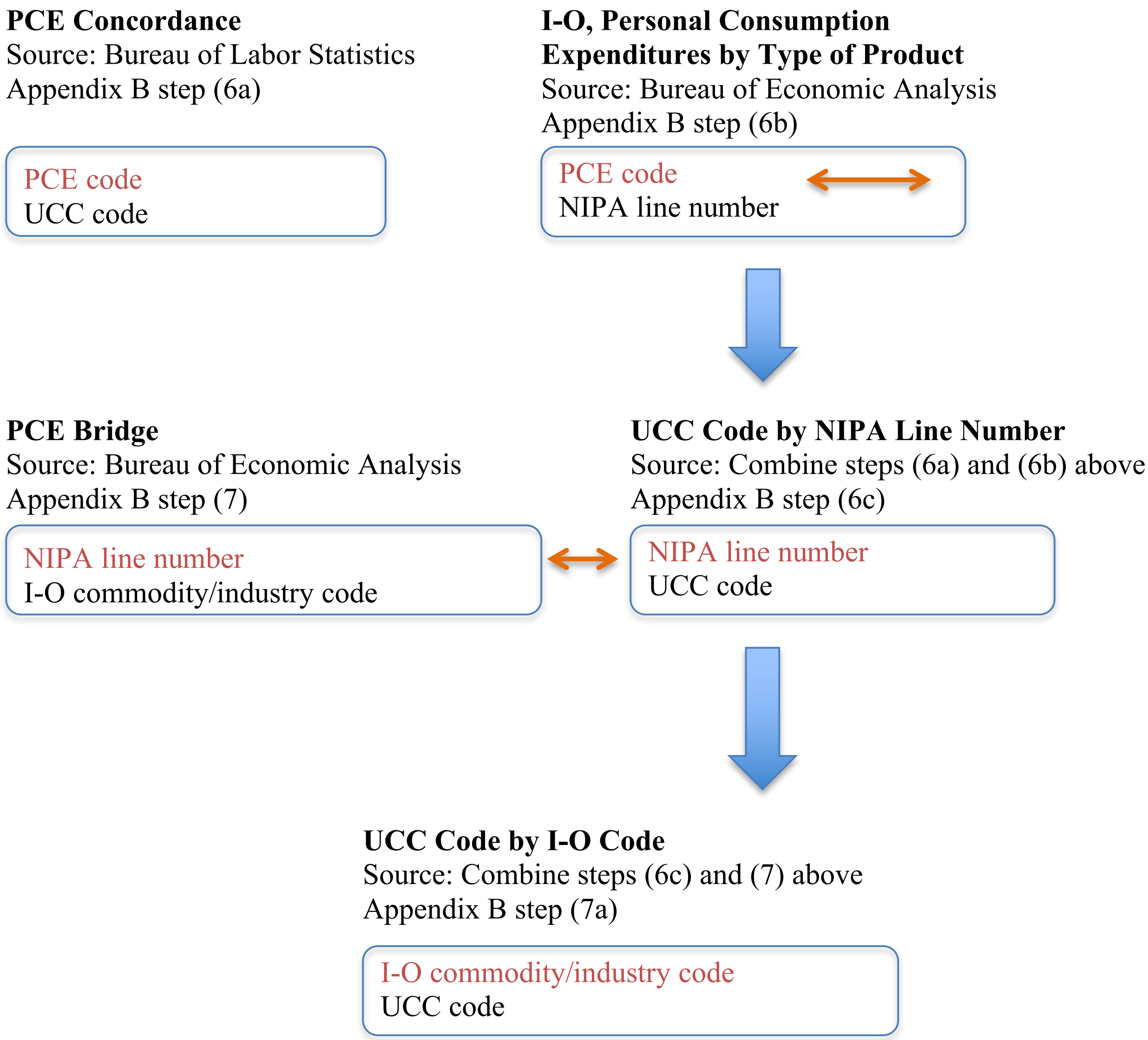


Figure B1. Mapping regulations onto input-output (I-O) codes



Note: NAICS = North American Industry Classification System.

Figure B2. Mapping input-output (I-O) codes onto consumer expenditure codes



Note: PCE = personal consumption expenditures; UCC = Universal Classification Codes; NIPA = national income and products accounts.