E-Commerce Effects on Energy Consumption
A Multi-Year Ecosystem-Level Assessment

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Summary
This research investigates the impact of e-commerce on energy consumption in all four sectors of the U.S. economy (commercial, industrial, residential, and transportation), using macroeconomic data from 1992 to 2015. These data capture all the development phases of e-commerce, as well as direct and rebound effects in and across sectors. Empirical dynamic models (EDMs), a novel methodology in industrial ecology, are applied to the e-commerce/energy relationship to accommodate for complex system behavior and state-dependent effects. The results of these data-driven methods suggest that e-commerce increases energy consumption mainly through increases in the residential and commercial sectors. These findings contrast with extant research that focuses on transportation effects, which appear less prominent in this investigation. E-commerce effects also demonstrate state dependence, varying over the magnitude of e-commerce as a percentage of the total retail sector, particularly in commercial and transportation realms. Assuming these effects will continue in the future, the findings imply that policy makers should focus on mitigating the environmentally deteriorating effects of e-commerce in the residential sector. However, this investigation cannot provide root causes for the uncovered e-commerce effects. Robustness of the empirical findings, limitations of the novel EDM methodology, and respective avenues for future methodological and substantial research are discussed.

Introduction
Public interest in the environmental side effects of online shopping appears to be growing—as evidenced by various headlines in the popular press published just in the first quarter of 2016 (e.g., “How green is online shopping?” [DeWeerdt 2016]; “What’s more eco-friendly: Going to the mall or shopping online?” [Pleven 2016]; “E-commerce: Convenience built on a mountain of cardboard” [Richtel 2016])—in parallel with the increasing share of e-commerce in the total retail sector, which reached 7.1% in the United States and 7.5% in Western Europe in 2015 (eMarketer 2015). Current developments continue to foster this growth, including the seamless integration across retail channels that enables customers to make convenient online purchases from brick-and-mortar stores (“omni-channeling”) (Verhoef et al. 2015) and the expanding promise of same-day delivery from online retail giants such as Amazon and Google. Therefore, the time is right for industrial ecology (IE) to assess the impact of e-commerce “bits” on the “atoms” of its physical environment (Rejeski 2002).
In theory, the environmental effects of all information and communication technology (ICT) can be distinguished as first, second, and third order (Fichter 2002; Erdmann and Hilty 2010). For e-commerce, first-order effects capture energy consumption by hardware (e.g., Amazon’s server farms), second-order effects entail the consequences of e-commerce due to substitution or process transformation (e.g., fewer visits to the mall but more cardboard boxes), and third-order effects cover changes in the system and related feedback effects. The first-order effects are burdensome to the environment, but mostly small (Laitner 2002). Most studies focus on the second-order effects, especially adjustments to the modes and magnitudes of personal travel and delivery in the transportation and distribution sector (for an overview, see Rotem-Mindali and Weltevreden [2013]). Many of these studies offer conflicting implications for environmental policy, even when investigating seemingly digital-friendly supply chains (e.g., digital versus physical media distribution) (Weber et al. 2010; Mayers et al. 2015), likely because life cycle assessments of second-order effects are sensitive to underlying assumptions and defined system borders (Fichter 2002; Edwards et al. 2010; Rotem-Mindali and Weltevreden 2013). Finally, the third-order effects are indirect feedback effects within the system (Hertwich 2005), as efficiency gains might be (partially) offset by consumers’ reactions through a “rebound effect” (Masanet and Matthews 2010). For example, if e-commerce increases the efficiency of a supply chain, the lower costs and prices could increase demand. E-commerce also alters consumers’ lifestyles (Erdmann and Hilty 2010); for example, it could shift their use of their spare time from going to the mall (Fichter 2002) to other energy-demanding activities. Thus, online shopping could result in long-term system changes (Ruzzenenti and Basosi 2010) that have vast, environmentally impactful repercussions. Therefore, to guide environmental policy, this study considers e-commerce effects and feedbacks as an ecosystem in their entirety (Allenby 1999; Masanet and Matthews 2010) and from a macro-level perspective (Erdmann and Hilty 2010).

Specifically, the present study provides an empirical, aggregate ecosystem-level investigation of online retail’s environmental effects, in response to calls for an e-commerce–specific, multiyear investigation (Laghaei et al. 2015). Few macroeconomic statistical models investigate the net environmental impacts of ICT more broadly, and those that do produce inconsistent results, some showing a beneficial influence (Romm et al. 1999) and others a differentiated influence (Kuhndt et al. 2003). These differences might reflect the different periods of investigation; to the best of our knowledge, no research details changing perspectives. For example, no extant studies offer a methodological approach that adopts a dynamic ecosystem perspective and accounts for state-dependent environmental effects.

The present article addresses these gaps and thereby contributes in four dimensions. First, by investigating monthly macro-level data from the United States for a period of 24 years (1992–2015), this article covers all the e-commerce development stages (infancy [i.e., early stages of e-commerce development], dot-com boom and bust [i.e., the boom phase of electronic businesses in the late 1990s until the crash of the digital economy in 1999], and omni-channeling [i.e., the current tendency of on- and offline retailers to integrate multiple sales channels]). Second, by assessing impacts in all sectors of national energy consumption—commercial, industrial, residential, and transportation—this investigation offers a holistic perspective and integrates different research streams (e.g., transportation and supply-chain efficiency). Third, this article introduces novel empirical dynamic models (EDMs) to the field of IE. This nonlinear, equation-free methodology can account for the complex ecosystem of many investigation objects in IE, as well as uncover state-dependent interaction effects empirically. Fourth, specific implications for future theoretical or empirical research, as well as for environmental policy, emerge from these findings.

### Energy Consumption Effects of Increasing E-Commerce

Increasing e-commerce affects many different sectors and variables in a socioeconomic system. The present study uses energy consumption to assess environmental effects, because it is physically more fundamental than greenhouse gas (GHG) emissions and less likely to differ structurally over time, as it is independent of the energy mix. Thus, investigating energy consumption produces robust results that can be adapted to policy changes to the energy mix.

Early studies of e-commerce effects predicted energy savings, anticipating that more energy-efficient warehouses would replace retail outlets (Romm et al. 1999). Yet, the first half of the commercial sector energy consumption data (1992–2003) available from the U.S. Energy Information Agency (US EIA), covering the early stages of e-commerce adoption, including the dot-com boom and bust, shows an annual growth of +2.1% on an absolute and +1.1% on a per capita basis. In the second half of the available data, the absolute energy demand continued to grow annually (+0.1%), although the trend changed on a per capita basis (−0.6%).

We can only speculate as to potential sources of this growth in energy demand, but multiple explanations are possible. First, additional demand might have been caused by a doubling of infrastructure, particularly for nascent e-commerce with little substitution of physical stores. Second, increasing retail energy demand could also point to a competitive offline reaction: Consumers seemingly shop for fun, seeking hedonic, multisensory experiences in retail (Hirschman and Holbrook 1982; Babin et al. 2012). For example, no extant studies offer a methodological approach that adopts a dynamic ecosystem perspective and accounts for state-dependent environmental effects.
et al. 1994), so offline retailers could have fought online competition by improving hedonic store elements (Childers et al. 2002). These elements might demand substantial energy, such as special lighting or spacious designs (Ballantine et al. 2010). Further, retailers increasingly offer seamless shopping experiences, in which on- and offline research and purchase channels complement, rather than substitute for, one another (Verhoef et al. 2007). Third, the commercial sector includes energy-demanding recreational services, which consumers might be increasingly consuming (e.g., based on the additional spare time from shopping online). Fourth, the commercial sector also includes the offices and data centers that grow with e-commerce and whose cooling and computation requires substantial energy (Lewis 2016). In summary, the net effect for the commercial sector thus could be negative or positive, depending on the magnitude of substituted offline retail, changing consumer demands and first- and second-order effects of e-commerce on the commercial sector.

Regarding the effects of e-commerce on industrial energy consumption, additional information should influence both producers (i.e., newly available customer data) and consumers (i.e., market transparency). On the one hand, online consumer behavior creates more knowledge for producers so they can reduce overproduction and inventory levels (Siikavirta et al. 2002). The digitalized supply chains also might be managed more efficiently (Matthews and Hendrickson 2002). These energy-saving effects could decrease as e-commerce penetration expands though, as the marginal knowledge and efficiency effects diminish. On the other hand, the Internet enables better market transparency, so consumers tend to find differentiated, niche products, creating fragmented and inflated, “long-tailed” demand for products (Brynjolfsson et al. 2011). The industrial sector then must produce more differentiated offerings with smaller lot sizes, which likely increases energy consumption. Therefore, the total effect of e-commerce on industrial energy consumption is unclear a priori.

Discussions about the effects of e-commerce on residential energy consumption center around third-order, or rebound, effects from consumers’ spare time and cost savings (Hilty et al. 2006). For example, lower prices might support increased consumption (Hertwich 2005), and additional leisure time can be spent at home or in public (Laghaei et al. 2015). Time at home likely creates additional energy demand for heating, cooling, lighting, or electrical devices; time spent in public places (e.g., shopping malls, cinemas) may reduce residential energy consumption, but place additional burdens on commercial or transportation sectors. In contrast, richer product information and on-demand or peer-to-peer purchasing could help lengthen product life cycles and reduce waste and consumption. Thus, the energetic net effect of e-commerce on the residential sector thus is not clear from extant literature either.

Most prior research addresses the effects of e-commerce on transportation and distribution, such as the effects of freight delivery versus individual pickups (Rotem-Mindali and Salomon 2007; Rotem-Mindali and Weltevreden 2013), “last mile” efficiency (Edwards et al. 2010), or local transportation systems’ reactions to e-commerce (Laghaei et al. 2015). Aggregate country-level studies indicate a slight decrease in transportation due to e-commerce (Weltevreden and Rotem-Mindali 2009), potentially moderated by population density and transportation modes (Matthews et al. 2002). The energetic net effect on the transportation sector is likely negative, but it ultimately depends on the mix of added or substituted instances and modes of transport, which could change over time and interact with online retail penetration. Consequently, because the effects of e-commerce on energy consumption are unclear in all four sectors, we investigate the net effects empirically.

Methodology

EDMs offer an interesting option for investigating the environmental effects of e-commerce because of their beneficial properties when modeling inter-related system effects. Specifically, modeling complex, inter-related effects empirically typically requires the researchers to specify the complete set of variables and their causal relations to describe the behavior of a system. Considering the vast number of economic, social, or physical variables that conceivably could exert influences on the energy system, it seems almost impossible to specify any “true” model of the influence of e-commerce on energy consumption.

Instead, EDMs take the reverse approach and infer system dynamics from any single variable in the system. Researchers have used EDMs to retrieve complex information from single variables in other systems, such as species abundance in a marine ecosystem (Dixon et al. 1999; Hsieh et al. 2008; Doyle et al. 2013), heart rhythm anomalies in human bodies (Sugihara and May 1990), or temperatures in the climate system (Van Nes et al. 2015). In some cases, EDM-based predictions even outperform estimated “true” parametric models for simulated systems (Perretti et al. 2013).

When using two variables from the same system, some EDM also can provide empirical confirmation of the direction of causal relationships between two variables, while ruling out alternative but omitted drivers. Prior applications of EDMs have successfully untangled causal relationships in contexts such as foodwebs (Sugihara et al. 2012), between cosmic rays and global temperature (Tsonis et al. 2015), and more recently in economic data (Huffaker and Fearne 2014), including macroeconomic links to e-commerce (Dost 2015).

Finally, EDMs can model nonlinear and state-dependent effects between causally related variables, which is particularly relevant for the effects of e-commerce growth. For example, the influence of e-commerce likely changes over time (because its first-, second-, and third-order effects occur at different speeds) (Ruzenenti and Basosi 2010) and is particularly sensitive to changes in the underlying system conditions (Rotem-Mindali and Weltevreden 2013). This state-dependent behavior features structural breaks and tipping points (May et al. 2008; McCann et al. 1998), which are the norm rather than exceptions in socioeconomic systems (e.g., Hsieh et al. 2005; May et al. 2008; Scheffer et al. 2009; Sugihara et al. 1996).
In such circumstances, correlation-based models typically fail (Boyd 2012; Liu et al. 2014), because two causally linked system variables may show, at various times, a positive, negative, or zero correlation (Lorenz 1963; Sugihara et al. 2012). In contrast, EDMs are not confined by the principles of linear correlation to model causation (Berkeley 1710), but instead adopt Takens’s (1981) embedding theorem. From these embeddings, EDMs estimate state-dependent interaction effects among variables (Deyle et al. 2013, 2016).

Principles and Concepts of Empirical Dynamical Models

All EDMs are based on the theory of dynamic systems (Deyle et al. 2013), according to which a system is not a set of time series, but rather an attractor manifold in a multidimensional system state space (Lorenz 1963; Sugihara et al. 2012). Figure 1 exemplifies this idea by showing a two-dimensional state space, in which two variables, the share of online retail and residential sector energy consumption, constitute the two coordinate axes. Over time, the trajectories of both variables together construct an attractor manifold in this state space. For a visual explanation, we recommend Sugihara and colleagues’ (2012) short video animation, which also graphically reconstructs an attractor manifold from time series data (https://youtu.be/8DikuwPW5sY).

To reduce system state representation to a few focal time series, or even a single variable, the EDM applies Takens’s (1981) embedding theorem for deterministic systems (see also Deyle and Sugihara 2011). Takens proves that information in a multidimensional, deterministic, dynamic system is embedded in the time series of any variable causally forced by that system. The vectors of a single variable and its own time lags—termed delay coordinate embedding or shadow manifold—thus can reconstruct the dynamics of the whole system (Sugihara et al. 2012; Jiang et al. 2016), as shown in panel c of figure 1 with residential energy consumption at times $t$ and $t-1$ on the coordinate axes of the shadow manifold. Another helpful video animation shows a similar shadow manifold reconstruction from a single system variable (https://youtu.be/QQwtrWBwxQg) (Sugihara et al. 2012).

In the manifolds, some vectors (i.e., system states) are close or proximal in state space; however, these vectors are not necessarily close along the overall trajectory and thus might not be close in time. All EDMs use the proximity between vectors in state space to make predictions, as depicted in panel a of figure 2 (adapted from Deyle et al. 2016). Panel b shows how this idea differs from traditional autoregressive or (dynamic) linear models that make predictions solely from data close in time (Deyle et al. 2016). Thus, unlike linear models, EDMs are not confined by correlation over longer stretches of time. For example, in panel c, trajectories develop in many directions, representing nonlinearly evolving variables with no consistent positive or negative correlation. In contrast, consistently linearly correlated variables would evolve along a common axis in state space.

The key model specification for EDMs, then, is not the appropriate selection of correlated time lags, as in linear models, but rather the appropriate selection of an embedding dimension $E$ (i.e., dimension of shadow manifold state space and the number of elements in the state vectors). Other different EDM-specific representations of common concepts or ideas in linear models are listed in table 1. For example, the vector library length $L$ in the EDM reflects the concept of data quantity, which in linear model terms is simply sample size $n$.

Relevant Empirical Dynamical Model Variants

The empirical study reported herein relies on three EDM variants, which in concept and purpose have equivalents in traditional linear modeling. They are used to, first, empirically establish EDM conditions for the investigated variables; second, to empirically test causality between variables; and finally, to empirically assess the magnitude of influence of the
The marginal effects of e-commerce on energy consumption can be estimated using empirical dynamic models (EDMs) and traditional linear models. EDMs leverage techniques such as simplex projection to predict energy consumption from data close in state space, whereas linear models estimate parameters from time series. EDMs are particularly useful for systems where the driving variable—in our case, the share of e-commerce—is coupled with energy consumption at different states.

EDMs include concepts like embedding dimension, which determines the minimum number of variables required for the model. The simplex projection method, for example, selects an optimal embedding dimension and establishes whether the variables show bidirectional causality. In this context, CCM—cross-mapping—can distinguish unidirectional from bidirectional causality, allowing for more accurate predictions of energy consumption influences from e-commerce.

Table 1: Comparison of EDMs and traditional linear models concepts

| Concept                        | In EDMs     | In linear models |
|--------------------------------|-------------|-----------------|
| Source data format             | Time series variables | Time series variables |
| Data representation            | Attractor manifold in state space, build from time series | Multiple parallel time series |
| Data input into a model        | Embedding manifolds/library of vectors | Multiple parallel time series |
| Data quantity used             | Library size: L | Sample size: n |
| Main model specification parameter/model order | Embedding dimension: E | Number of time lags, e.g., in a vector-autoregressive model (VAR) |
| Model prediction principle     | Trajectories of vectors close in state space | Correlation; values close in time |
| Univariate prediction          | Simplex projection | Univariate autoregressive model |
| Empirical causality test       | Convergent cross-mapping (CCM) | Granger causality |
| Dynamic marginal effect estimation | Multivariate S-maps—estimate state-dependent effects | Dynamic linear models (DLM)—estimate time-dependent effects |

Note: EDM = empirical dynamic models.
### Table 2  Overview of variables and data

| Variable name                  | Description                                                                 | Source                                | In study | Unit     | Mean  | SD    |
|--------------------------------|------------------------------------------------------------------------------|---------------------------------------|----------|----------|-------|-------|
| Total retail sales             | Total monthly sales, not seasonally adjusted                                 | U.S. Census Bureau                     | 10⁶ USD  | 276,369  | 76,027|       |
| Online and mail-order sales    |                                                                              |                                       |          | 14,733   | 10,053|       |
| Online retail share            | Online retail sales divided by total retail sales                             | Calculated                            | x        | %        | 4.8   | 2.2   |
| Commercial energy consumption  | Total monthly energy consumption by sector, not seasonally adjusted          | U.S. Energy Information Administration| x        | 10¹² BTU | 1,402 | 168   |
| Industrial energy consumption  |                                                                              |                                       |          |          | 2,714 | 158   |
| Residential energy consumption |                                                                              |                                       |          |          | 1,688 | 365   |
| Transportation energy consumption|                                                                             |                                       |          |          | 2,183 | 170   |
| Total energy consumption       | Sum of all energy consumptions                                               | Calculated                            | 10¹² BTU | 7,986    | 581   |       |

Notes: Monetary units in millions of U.S. dollars (USD). Energy consumption is the total—not just primary—energy consumed by the commercial, industrial, residential, and transportation sector. It is measured in trillions (10¹²) of British Thermal Units (1 BTU ≈ 1.05506 kJ). SD denotes standard deviations.

variables at the same time, thus violating separability (Sugihara et al. 2012).

Interestingly, CCM converges to the actual cross-prediction correlation over larger library sizes, which helps guard against omitted variables or *mirage correlations* (Sugihara et al. 2012; Ma et al. 2014). For example, if energy consumption were not driven by e-commerce growth and both variables resulted only from overall economic growth or efficiency trends, cross-prediction correlations would converge to zero. In contrast, if CCM cross-prediction correlations converge on a significantly positive value, it indicates deterministic causal coupling between the variables.

Third, to estimate state-dependent marginal effects, Deyle and colleagues (2016) propose the S-maps procedure (Sugihara 1994, 1996; Dixon et al. 1999). The present study modifies this procedure to produce more conservative effects (Sugihara 2016) and to concentrate on a few focal variables, as the “true” causal system is unknown. Specifically, a focal variable (here, the online retail share) is combined with the whole shadow manifold of the target variable (e.g., residential energy consumption). Such a multivariate embedding captures the dynamics of the complete system (Takens 1981) and implicitly controls for all omitted causal system variables (e.g., efficiency trends, economic growth), which are unknown. The idea is similar to Deyle and colleagues’ (2013) scenario exploration approach, which also applies S-maps (for additional details, see the Supporting Information on the Web and explanations in the empirical investigation).

The R code to calculate marginal effects from multivariate embeddings is available in Deyle and colleagues (2016). Simpex projection, CCM, and S-maps functions are in the rEDM R-package by Ye and colleagues (2016). Using these sources, the empirical study reported herein uses all three methods to investigate the state-dependent marginal effects of e-commerce on energy consumption with macroeconomic time series data.

### Empirical Study

The empirical database for this study consists of U.S. national, monthly time series data for a period of 24 years, from January 1992 to December 2015, with 288 data points per variable (see table 2). The focal variable—online retail share—reflects total U.S. home shopping retail sales in dollars, divided by the total amount of all retail sales. The variable also includes mail-order shopping, because “pure online” retail data are reported only quarterly and only starting in 2000. The calculated online retail shares thus are consistently approximately 2 percentage points higher than reports of pure online e-commerce indicate. The online retail share variable used herein captures all out-of-home shopping activities, which likely affect energy consumption similarly (except the different but small first-order effects of ICT). A robustness test with a monthly variable corrected by the respective quarterly difference also did not produce substantially different results. Therefore, this study reports the monthly ratio of online and mail order shopping to total retail as the “online retail share.”

### Confirming Empirical Dynamical Model Conditions

Simplex projections over different embedding dimensions $E$ reveal the good univariate predictability of all five variables. The univariate forecasts use leave-one-out predictions, but
remain robust when using twofold cross-predictions instead. The best forecast skill levels \( \rho \), measured as the correlation between target values and the forecasted values, are all close to \( \rho = 0.9 \) or beyond, as shown in figure 3. This result indicates that all variables have dynamic system behavior embedded in their history.

The best embedding dimensions are typically around \( E = 12 \), which could be expected from monthly data, but the first skill level peaks or plateaus emerge at smaller embedding dimensions of \( E = 6 \) or \( E = 7 \). To balance a good representation of embedded system information with parsimonious model vectors, these smaller \( E \) values are selected for the energy consumption variables in the CCM and S-map models. Robustness checks with the larger \( E \) value reveal no substantially different results.

### Determining Causal Couplings

The CCM cross-predictions suggest causation between online retail share and each of the four energy consumptions. Causal forcing is empirically established if the leave-one-out cross-prediction correlations \( \rho \) (CCM skill) improve with more data (i.e., over increasing library sizes \( L \)) and converge to a value larger than zero (Sugihara et al. 2012; Ye et al. 2015). As library sizes \( L \) in this study are larger than in extant empirical studies from ecology (e.g., Sugihara et al. 2012), and given the shape of the plots for all four variable pairings in figure 4, we are confident that convergence has been reached. There is, however, no formal statistical test for it. Bootstrapping each \( \rho \) 100 times (with replacement) for each \( L \) provides estimates of the standard deviations and 99% confidence intervals (dashed lines in figure 4). All four plots show convergent and significant cross-prediction correlations and thus suggest causal effects from online retail share to energy consumptions. Specifically, the CCM skills converge at \( \rho = 0.78 \) for the commercial sector, \( \rho = 0.86 \) for the industrial sector, \( \rho = 0.65 \) for the residential sector, and \( \rho = 0.66 \) for the transportation sector.

Summing up, all CCM results seem to confirm the causal direction from e-commerce to energy consumptions, but the estimated cross-correlations do not yet indicate sign or magnitude of the marginal effects between the variables, which only the next step will provide.

### Estimating State-Dependent Marginal Effects

The multivariate S-maps procedure calculates marginal effects (direction and strength) from a manifold that adds online retail share as an additional predictor to the shadow manifold of the respective energy consumption. With energy consumption as target variable and online retail share as additional predictor, marginal effects in each system state take the form:

\[
\text{marginal effect} = \frac{\delta \text{ energy consumption (in 10}^{12} \text{ BTU)}}{\delta \text{ online retail share (in %)}}.
\]

For example, a marginal effect of +19 in the commercial sector would signify an increase in commercial energy consumption by 19 trillion British Thermal Units (BTU) as a result of a 1 percentage point increase in the e-commerce share.

For the state-dependent marginal effects, precise S-maps predictions require a well-tuned nonlinearity parameter \( \theta \). The S-maps parameter \( \theta \) tunes how strongly the estimates are localized to the state space vicinity of the target vector. If the \( \theta = 0 \), then S-maps reduces to a constant coefficient model, indicating linear dynamics, but if \( \theta > 0 \), then the S-map
coefficients can vary across state space. Thus, an optimal $\theta > 0$ signals nonlinearity and prevalent state-dependent interactions, further strengthening the argument for EDMs in the first place (Sugihara 1994; Deyle et al. 2016). The S-map predictions for the four estimated models at different values of $\theta$ are presented in figure 5: S-map prediction skill improves when $\theta$ is greater than zero, indicating the presence of state-dependent interaction effects. Only the residential energy consumption model shows almost linear effects (best $\theta = 0.05$), implying a near constant effect in all system states.

The marginal effects at each system state (i.e., level of e-commerce) on the energy consumptions by sector are estimated using the respective best parameter $\theta$ (see figure 5), and then averaged to provide a total marginal net effect over all data points, as well as averaged over the most recent year (2015) to provide a current marginal net effect (see table 3). The sum of all average marginal effects, which represents the total net effect on energy consumption, is positive with +48.6 trillion BTU for each additional percentage point of total retail represented by online retail. Increasing online retail share thus seems to have, on average, increased energy consumption over the past 24 years, by roughly +0.61% per each additional percentage point.

Increasing e-commerce affects energy demand in all the four sectors differently. Because prior results suggest state-dependent marginal effects, figure 6 plots the marginal effects over online retail shares. It also shows polynomial regressions to trace the mean levels over time. All marginal effects appear, at least for some system states, significantly positive or negative. Except for the residential sector, all marginal effects also indicate state-dependent behavior.

Based on these results, e-commerce has affected energy consumption in the commercial and residential sectors most severely, with marginal effects that increase sectorial energy consumption by more than 1% on average for every additional percentage point of online retail. The marginal effect on the commercial sector decreased over time from +25 to now +18 trillion BTU per percentage point of additional e-commerce (see figure 6a). The marginal effect on the residential sector has been stable at around +33 trillion BTU per percentage point (figure 6c)—the single strongest marginal impact. Though we can only guess, possible explanations might comprise behavior shifts toward other energy-demanding activities in the time formerly spent shopping offline.

Both industrial and transportation sectors signal beneficial (negative) net marginal effects of online retail share, though these effects seem comparably small. The small beneficial effect on the industrial sector seems to have leveled out to around zero with growing online retail (figure 6b). Figure 6d shows the highly state-dependent marginal impacts on the transportation sector, displaying harmful marginal effects for low initial,}

![Figure 5 Correlations of predictions versus observed values over the tuning parameter $\theta$ using multivariate S-maps. Embedding vectors are of the form $(\text{Energy}_1, \ldots, \text{Energy}_{E-1}, \text{OnlineRetailShare})$. Circles mark the optimal tuning parameter $\theta$. The variables, except residential energy consumption, show improved predictability at $\theta > 0$, indicating nonlinearity.](image)

| Marginal effect by energy sector | 1992–2015 | 2015 only |
|-------------------------------|-----------|-----------|
|                              | Mean ($10^{12}$ BTU/%) | SD ($10^{12}$ BTU/%) | Relative change | Mean ($10^{12}$ BTU/%) | SD ($10^{12}$ BTU/%) | Relative change |
| Commercial                    | 19.1      | 2.9       | +1.36%      | 17.8      | 2.2       | +1.18%      |
| Industrial                    | -2.4      | 2.0       | -0.09%      | -0.4      | 0.7       | -0.02%      |
| Residential                   | 33.4      | 0.3       | +1.98%      | 33.7      | 0.7       | +1.92%      |
| Transportation                | -1.4      | 4.8       | -0.05%      | -5.3      | 1.8       | -0.23%      |
| Total energy consumption      | $\Sigma = 48.6$ |                        | +0.61%      | $\Sigma = 45.8$ |                        | +0.56%      |

Notes: Marginal effect = $\frac{\text{energy consumption in } 10^{12} \text{ BTU}}{\text{percentage change}}$. Relative change is the estimated change in total energy consumption in the respective sector due to an increase in the online retail share by 1 percentage point, relative to absolute total energy consumption in the sector in British Thermal Units (BTU). SD denotes standard deviations.
but beneficial effects for higher current levels of online retail share.

**General Discussion**

**Critical Discussion of the Results**

Four characteristics of our assessment may have influenced the findings described herein: the time period of the analysis, possible estimation errors associated with the method, inadequate data, and the focus on causal relations between only two variables, not explicitly controlling for alternative explanations. The following discussion elaborates on these characteristics and the extent of their effects on our study.

First, this marginal effects estimation is based on the entire period of e-commerce development (1995–2015) and thus includes early phases in which supply and demand used online and offline retail in parallel (e.g., no reduction in physical store space and an increasing number of online stores; drive to the mall and shopping via e-commerce). As online retail share...
grows, more retail and personal activities are substituted and the additional energetic impact of e-commerce decreases. In line with this conjecture, the marginal effects of e-commerce on energy consumption have steadily fallen with the increasing importance of online retailing. Indeed, as of 2015, the total marginal effect of e-commerce leveled out at approximately +46 trillion BTU per e-commerce percent—a 6% improvement over the total average. The impact in the residential and industrial sector remained the most stable over time, while the transportation sector showed further improvements (−5.3 in 2015 vs. −1.4 on average). The state-dependently changing marginal effects in the transportation sector are also not unexpected, as extant research suggests mixed results regarding ICT effects on transportation (Matthews et al. 2002).

The marginal effects of e-commerce on the commercial sector have declined over time (+17.8 in 2015 vs. +19.1 on average). However, we have to be cautious with drawing implications for the commercial sector for a number of reasons: First, two economic crises alongside a continuous growth in population size coincide with our assessment period, impacting commercial energy consumption. Second, several trends within the commercial sector (e.g., changes in stationary retail, the growth and decline of shopping malls, changing service demand, or increasing data center use) affect commercial energy demand individually or jointly. EDMs implicitly account for the impact of external trends; additionally, when explicitly controlling for population size and gross domestic product (GDP) development, the results remained robust. With the current macro-economic data, however, we cannot investigate the mechanisms for the estimated positive effect of e-commerce on the commercial sector in detail. Thus, our findings on the commercial sector may appear less intuitive than those in the other sectors, mandating caution when deriving policy recommendations.

Second, the estimated marginal effects may exhibit errors, although Deyle and colleagues’ (2016) simulations suggest robust estimations and low errors of the S-maps procedure. In these simulations, the smallest correlation between actual and estimated effects was still approximately 0.5 (see figure S8 in Deyle et al. [2016]) for a complex simulated system with five causal variables and a sample size of n = 300. Thus, in this empirical study with simpler models and comparable sample sizes, errors in estimated marginal impacts are likely comparably small. Still, a remaining error could systematically shift the marginal effect plots slightly upward or downward. The industrial sector results (figure 6b) are closest to zero and hence would be the most vulnerable to such an error, because it could have affected the interpretation as positive or negative marginal effect. Furthermore, the multivariate S-maps predictions had the lowest forecast skill levels (forecast skill levels = 0.53; see figure 5) for the industrial sector model. Therefore, although the suggestions regarding the industrial sector seem the least certain, they also have the smallest consequences in terms of mistaken effect sizes. Transportation sector results are also close to zero; however, in our study, multivariate S-maps showed the best forecast skill (0.79), and thus they likely exhibit smaller errors. In summary, it seems unlikely that estimation errors could have caused dramatically different results.

Third, S-maps, as all EDMs, is an empirical, data-based method. If input data are inadequate (e.g., comprised of unreliable or invalid measures of the focal variables), the results could be inadequate as well. In line with extant research (Raichur et al. 2016; Ngo and Pataki 2008), we relied on monthly statistics from the US EIA and hope that the data are reliable, despite smaller changes in the methodology of the commercial energy use surveys published by the same institution (US EIA 2003).

To address reliability concerns, this study applied a step-by-step procedure, including CCM to empirically establish the existence of all investigated relationships and effects. As previously described, CCM theoretically converges toward the true value with more data. The respective tests in this study seemed to confirm convergence over the present data, indicating a reliable effect between the used variables. Moreover, CCM reacts conservatively to measurement errors in the data or process noise in the system. Extant simulation studies have revealed reductions in both type I and II errors for increasing errors in simulated data (Clark et al. 2015). Thus, finding convergence to a significantly positive cross-correlation is a robust indicator of actual causal forcing. Large cross-correlations, however, could also result from synchronized variables. Synchrony can occur when one variable causally forces another so strongly that the latter becomes “enslaved” to the former (Sugihara et al. 2012; Clark et al. 2015; Ye et al. 2015). In this case, CCM would falsely return bidirectional causality for a unidirectional causal process. In the current study, a possible reverse causal forcing from energy consumption to online retail share, enslaving the latter, seems unlikely. Even if some effect from energy consumption to e-commerce utilization occurred (e.g., via price or demand effects), it is probably not the strongest driver and thus unlikely to synchronize consumers’ online shopping behavior solely to patterns of energy consumptions. Thus, an actual reliable effect is highly likely in this study. In summary, we cannot rule out invalid measures, but simply trust in the measures on which numerous previous studies and policy evaluations are based.

Fourth, alternative omitted variables could have produced or altered the estimated results. However, demonstrated convergence in the CCM tests provides a sound empirical argument against the possibility of an omitted alternative driver similarly affecting e-commerce and energy consumption and thus producing a "mirage correlation" (Sugihara et al. 2012; Ma et al. 2014). Convergent positive cross-correlations indicate at least some (potentially mediated) effect of e-commerce on energy consumption. Still other omitted causal drivers (e.g., energy efficiency gains, economic trends, and the relocation of production to other countries) could have slightly affected the marginal effect estimates in S-maps. One of the major advantages of EDMs is that such omitted drivers are indirectly controlled for; following Takens’ (1981) theorem, they are empirically included in the reconstructed shadow manifolds of the dependent
variable (Sugihara et al. 2012; Deyle et al. 2013). Nevertheless, future studies could improve the effect estimates by explicitly accounting for other drivers—if available in similar granularity and reliability and independent from the others.²

**Limitations and Future Applications of Empirical Dynamical Models**

The presented methodology is novel to the field of IE; therefore, this article points to some general limitations as well as future applications of EDMs in this field. Although EDMs’ parsimony and robustness are interesting tools to spur empirical investigations of complex system effects from few available variables, they are by no means a “magic wand” that can solve all empirical problems. All the limitations discussed previously—possible estimation errors, reliance on the quality of the data, and potential omitted variables—generally apply for all EDMs.

The characteristics of EDMs render certain research fields more prone to the application of the method than others. First, EDMs have been developed for analyzing deterministic complex systems, in which small changes in one variable can cause the entire system dynamic to change, in contrast to linear systems, in which the relationships are stable and errors stochastic. Second, it is an empirical method, which does not require a theory-based specification of a model. Consequently, it can be ideally applied to research areas with conflicting findings and hypotheses or those in exploratory or early stages in the theory-building process. Third, because EDMs conduct the causality assessment with a parsimonious set of variables, research areas with limited availability of granular data or many unobserved variables would profit most from EDMs. Recent research areas that match one or more of these criteria include the climate effect of biofuels (Plevin 2016) and the cross-sectoral demand for production inputs (e.g., for phosphorus) (Hamilton et al. 2016).

Because EDMs have been developed to simultaneously account for all first-, second-, and third-order effects in a system, this feature also limits the insights the models can generate. In this article, EDMs only allow for establishing the gross (rebound) effects of e-commerce on energy consumption, without disaggregating different types of the rebound effect (Freeman et al. 2016). The present research is also limited to a national assessment; the results cannot be broken down to states, counties, or cities with different infrastructures or different consumers. Recent research instead notes the relevance of granular studies, particularly regarding residential energy consumption (Pincetl et al. 2016). Further, research should aim at disentangling the routes of the energetic effect of e-commerce. Current advancements in EDMs show some promise in identifying the sequence of several mediating variables in simulated systems (Ye et al. 2015), given sufficient time series data. In summary, we hope this article raises researchers’ curiosity to investigate the drivers of the effects of e-commerce or to apply EDMs to other areas of research and should be regarded as a starting point rather than a concluding remark.

**Conclusion**

Extant literature offers varying predictions about the effect of e-commerce on energy consumption, in general and for specific sectors. The current study offers an empirical indication that U.S. online retail share has contributed substantially to increasing energy consumption in the past. However, as the methodology is novel to the field of IE and does not shed light on the underlying drivers of this effect, further investigations are required to substantiate this finding. The marginal effects of the present investigation indicate that a hypothetical increase of online retail share by another 10 percentage points to roughly 20% of total retail would be projected to increase total energy consumption by approximately 5.6% compared with 2015. Our results propose that this effect would mainly stem from increases in residential (59% of the sum of absolute effects) and commercial (about 34%) energy consumption. Whereas extant research mostly addresses the transportation sector, the results from this study put the residential sector firmly on the environmental policy map.

This study also reveals state-dependent effects of e-commerce on energy consumption, varying according to the importance of online retail relative to the total retail sector. For instance, the marginal effects on commercial energy consumption appear to have decreased or leveled out, likely reflecting the initially stronger energetic burden of setting up an e-commerce infrastructure. The persistent positive impact may reflect offline retailers’ efforts to improve customer experiences and combat online competition, in which case the impact on the commercial sector likely will remain high and positive with increasing online retail shares, because any increase in online retail share represents additional competition. This article also reports substantial state dependency for the previously most often studied transportation sector. The estimated impacts show increasing energy consumption initially, but at intermediate levels of online retail share (approximately 5%, with 3% for pure online), a “sweet spot” emerges with negative marginal impacts. This effect has become weaker over time, and its future trajectory is uncertain. Current developments emphasize this uncertainty, suggesting the need for ongoing research. For example, consumers increasingly use energy-friendly local collection and delivery points (Collins 2015), but online shopping return rates also have been increasing (Hjort and Lantz 2016). Moreover, retailers and logistics companies are likely to comply with energy-intensive customer demands (de Koster 2002), such as those for delivery speed (e.g., Amazon Prime, Google Express) or novel delivery modes (e.g., autonomous drone).

Developing detailed policy recommendations from the current study is difficult, as it only quantifies the effect of e-commerce and does not detail the drivers of the trends. Given the state-dependent effects, an important research direction involves the moderators of the e-commerce/energy consumption relationship, possibly urbanization and population density (Matthews et al. 2002), the dominant freight transportation mode (Weber et al. 2008; Zhang and Zhang 2013), climatic conditions, or public income, wealth, and education.
Still, the broad macroeconomic level of assessment in this study can help identify energy conservation priorities (Williams and Tagami 2002). Faced with increasing online retail, this study indicates that policy makers should focus on the residential sector. Efforts to address the second strongest impacts, which emerge in the commercial sector, would likely create conflict between environmental policy interests and offline retailers’ profit or even survival; in contrast, in the residential sector, consumers’ general environmental and economic interests seem more aligned with policy interests. Here, consumer education, residential energy efficiency programs, or shifts in energy supply could help mitigate the e-commerce consequences for GHG emissions. This finding contrasts with current consumer-oriented efforts that focus on transportation (e.g., e-mobility). Finally, an interested public seeking a “greener footprint” should recognize that it might not be the delivery trucks and cardboard boxes, but rather their uses of their own time, be it on the move, seeking pleasure at a mall, or staying at home, that create the most additional energy consumption.

Notes
1. Granger causality is the linear model counterpart to CCM and a common causality test in time series models. In simplified terms, if a predictor variable X is excluded from a multivariate autoregressive model of target variable Y, and predictability of Y suffers as a result, then this is taken as evidence for the causal influence of the excluded variable.
2. When focusing on estimating marginal effects, however, these additionally included drivers should ideally be independent from one another because otherwise the procedure presented here estimates only the remaining marginal effects beyond all other drivers while these are held constant. If the drivers are inter-related, focal marginal effects should then be averaged or plotted over all possible states of the other drivers to account for the joint effects and still produce the full pattern of effects (Deyle et al. 2016). Thus, inter-related drivers can severely complicate the interpretation of results.

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Supporting Information

Supporting information is linked to this article on the JIE website:

Supporting Information S1: This supporting information provides the technical details for the empirical dynamic models (EDMs) used in the main article. Specifically, it describes simplex projection as a univariate prediction model, convergent cross-mapping (CCM) as a bivariate causality test, and S-maps as a multivariate model to estimate system state-dependent marginal effects. The descriptions build on the concepts and principles of EDMs as brought forth in the main article, but add the technical details necessary to run or program the model estimation algorithms.