The Impact of E-Commerce on Relative Prices and Consumer Welfare*

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Abstract

Using Japanese data on intercity prices and expenditures by retail outlet type, we find that the entry of e-commerce firms reduced the rate of price increase for goods sold intensively online relative to other goods, and significantly reduced intercity price dispersion of goods sold intensively online but had no effect on other goods. We overcome endogeneity issues by using historical catalog sales as an instrument for e-commerce sales intensity and estimate that reductions in price dispersion raised welfare by 0.3 percent. E-Commerce also lowered variety adjusted prices on average by 0.9 percent, and more in cities with highly educated populations.

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KEYWORDS: e-commerce, trade, prices, arbitrage, variety

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1 Introduction

How has e-commerce affected prices and consumers? One of the challenges in answering this question is that researchers typically only have short time series that do not allow them to compare pricing dynamics before and after the advent of e-commerce. Thus, while we can observe how the pricing dynamics of goods sold intensively online differs from those not sold online, it is difficult to assess whether any differences arise due to the advent of e-commerce or because of inherent differences in the pricing behavior of the goods themselves. This issue is particularly relevant because the types of products sold intensively online—books, clothing, electronics, and hardware—are also the types of goods that used to be sold intensively through catalogs. Thus, evidence about different pricing dynamics for these types of products is not necessarily evidence that e-commerce *caused* these pricing dynamics.

In order to resolve these issues, this paper makes use of a unique Japanese data set covering price quotes for the set of goods that make up the Japanese consumer price index (CPI) over the period 1991 to 2016 to examine the impact of the internet on Japanese relative prices and consumer welfare. We merge these data with Japanese government survey data documenting the share of consumption expenditures for each good occurring through each retail channel: catalog, e-commerce, and physical store. The long time series enables us to control for pre-trends in the pricing dynamics of the types of goods available from online merchants. Second, we are also able to use historical catalog sales as an instrument to correct for possible endogeneity bias arising from the fact that the entry of e-commerce merchants might be correlated with pricing behavior or our measure of e-commerce sales intensity might be measured with error.

We find that goods sold relatively intensively online have significantly lower relative rates of price increase. While one might be tempted to attribute this to the impact of online merchants, we exploit the long time series in our data to show that this pattern was also true before e-commerce firms entered the Japanese market. Thus, the differential pattern in pricing behavior seems to be a characteristic of the types of goods amenable to online sales rather than a feature of e-commerce. Nevertheless, we document that after the entry of e-commerce merchants, the difference in rates of price increase rose between goods not sold intensively online and those sold intensively, suggesting that e-commerce increased the difference in relative rates of price increase.

Second, we document that e-commerce had important impacts on rates of intercity price differentials. Following Cavallo (2018), we argue that e-commerce is a technology that promotes uniform pricing across locations. As such, we should expect to see the rate of intercity price arbitrage rise for goods sold intensively online but not for goods sold principally in physical stores. This is exactly what we observe in the data. While we find that prior to e-commerce intercity price differentials dissipated a similar rates for the sets of goods that would eventually be sold online compared to those goods that were never sold much online, after the advent of the internet, we find that intercity price differentials dissipated rapidly for goods available online but not for goods sold mostly in physical stores.

Based on our estimates of how e-commerce differentially affected the ability of merchants to price discriminate across cities, we compute the impact of e-commerce on Japanese consumers using the model developed in Jensen (2007). Jensen (2007) showed how one can measure welfare gains for consumers when information technology reduces regional price dispersion. While he applied this to cell phones in India, we adapt his framework to e-commerce by modeling it as a technology that reduces intercity price dispersion by enabling consumers to purchase the cheapest version of a good from any merchant selling online. We estimate the consumer gains due to e-commerce to be 0.3 percent of consumption expenditure in 2014 in our baseline specification.

In addition to the gains arising from improved price arbitrage across cities, we also compute the consumer gains due to new varieties. We model goods purchased online as new varieties either because they were not available locally before the advent of e-commerce or because an online shopping experience differs in important ways (convenience, service, etc.) from an offline shopping experience. As Brynjolfsson et al. (2003) and Dolfen et al. (2019) have argued, these variety channels are likely to be quite important and follow them by modeling e-commerce as a new method of conducting retail purchases. In order to address these concerns, we also use the approach developed in Feenstra (1994) to compute the gains due to varieties. We estimate that e-commerce lowered the price index faced by consumers by 0.9 percentage points by creating a new and better way of shopping. Interestingly, we also find evidence of a digital divide in terms of which consumers benefit the most from new varieties. Since e-commerce expenditure shares are highly correlated in Japan with college education, these gains accrued far more in cities with populations with a high share of college graduates like Tokyo than in cities with low levels of college education

1.1 Related Literature

Our results are related to a number of papers related to how information technology has affected pricing and welfare. A large literature has demonstrated that information technology serves to reduce price dispersion and promote trade. Freund and Weinhold (2004) show that countries with more web hosts export more to each other. Jensen (2007), Aker (2010), and Allen (2014) examine the impact of the introduction of mobile phones on fish or agricultural markets in India, Niger, and the Philippines, and Steinwender (2018) examines the impact of the transatlantic telegraph cables on 19th century textile prices and exports. Our work is complementary to these papers in that we also show that e-retail serves to reduce price dispersion. However, our work differs in focus and scope—our study examines the role played by e-commerce in an advanced, modern economy on the prices of hundreds of goods in physical retailers. The paper also relates to the literature on internet pricing. In particular, Cavallo (2017) shows that online prices and prices in physical stores are quite similar. This fact helps motivate our assumption that local retailers with high prices should face stiff competition from online retailers.

Our paper is also related to studies of the impact of e-commerce on welfare. Many of these studies have focused on the gains from variety that arise as consumers can purchase products that are not available in local stores. For example, Brynjolfsson et al. (2003) compute the variety gains from internet book sales, Fan et al. (2018) examine the relative variety gains in large and small Chinese cities associated with internet usage; and Dolfen et al. (2019) estimate the gains from e-retail due to shopping convenience and new varieties in the U.S. An important difference between these studies and ours is that we make use of household survey data to measure e-commerce sales shares for all goods in Japanese expenditures, and we deal with the endogeneity of e-commerce entry by using historical catalog sales.

Other papers have examined how the internet affects local markets. Goldmanis et al. (2010) examine regional patterns in online purchase behavior change the market structure in bookstores, travel agencies and car dealers. Goyal (2010) finds that the introduction of internet kiosks raised soy prices in rural India. Couture et al. (2018) conduct a randomized control trial in eight rural Chinese counties and find little effect of the introduction of e-commerce on the local economy. Brown and Goolsbee (2002) show that the creation of online insurance sales systems reduced the variance of insurance pricing. Our work differs from these studies in terms of scope (the large number of different sectors considered), the link to physical retail prices across an entire economy, and identification strategy (the ability to examine differential rates of price convergence before and after the advent of e-commerce).

Finally, our paper is also related to the large literature on PPP convergence regressions. Parsley and Wei (1996) were the first to document that differences in convergence coefficients across cities was linked to trade costs, an insight that we build upon in this paper. We estimate that intercity convergence rates for Japan pre-Rakuten are higher than those obtained in Parsley and Wei (1996) and Cecchetti et al. (2002). These studies found no price convergence across U.S. cities once one controlled for city fixed effects. In contrast, we find that prior to the advent of e-commerce, the half-lives for price differentials across Japanese cities were only 4.5 years. Our ability to better detect intercity price convergence probably arises from the fact that Japanese CPI data is based on the sampling of identical or extremely similar goods across cities, whereas U.S. price data is based on similar but non-identical sets of goods across cities. Moreover, we find that after the entry of e-commerce firms the half lives of goods sold intensively online collapsed to just a few months whereas goods not sold much online experienced no similar change. Our approach also builds off Bergin et al. (2017), who employ a similar triple difference strategy to show that rates of price convergence across European countries increased after joining the euro area.

The remainder of the paper is organized as follows. Section 2 introduces the the estimation strategy and provides the theory for the welfare calculation. Section 3 presents the data and provides some stylized facts about e-commerce suitability. Section 4.1 presents our results on national prices. We present our main estimates for the impact of e-commerce on price convergence and welfare in Section 4.2.. Section 4.3 presents our calibration of the new trade theory models, and Section 5 concludes.

2 Theory

In Section 2.1, we model the impact that e-commerce has had on interregional price differentials and show how the decline in these differentials raises welfare in Section 2.2.

2.1 Estimating the Impact of the E-Retail on Price Arbitrage

We begin by defining some notation. Let $p_{ict} \equiv \ln P_{ict}$ be the log price of item i in city c in time t. Define the Δ^k operator as $\Delta^k p_{ict} \equiv p_{ict} - p_{ic,t-k}$; thus, if we set $k = 1$, we can examine annual changes, but we can also examine longer differences by setting k equal to a whole number larger than one. Let $x_{ib}^E \in [0, 1]$ be the "e-commerce sales intensity" of a good measured in a survey year b, where zero indicates it is not suitable for e-commerce and one indicates that it is the most suitable good for e-commerce. Let D_t be an indicator variable that is one if e-commerce is an option in period t and zero otherwise. We assume that the change in the price of any item in a city c can be written as a standard purchasing price parity specification in which the rate of price convergence depends on their availability online , i.e.,

$$\Delta^k p_{ict} = \alpha_{it} + \beta_{ct} + \left(\gamma + \delta_1 x_{ib}^E + \delta_2 D_t x_{ib}^E\right) p_{ic,t-k} + \epsilon_{ict}. \tag{1}$$

In this specification, α_{it} is an item-time fixed effect; β_{ct} is a city-time fixed effect; γ is a parameter that captures the rate of intercity price convergence for goods not available online; δ_1 is a parameter that captures the rate of price convergence for goods available online prior to the entry of e-commerce firms; δ_2 captures the increase in rate of price convergence for online goods after the entry of e-commerce firms; and ϵ_{ict} is an iid error term. We think of this error as price shocks arising from period t local supply-and-demand conditions for an item in a city that are not shared by all items in the city and are uncorrelated with past prices.

The rate of convergence is given by $\left(\gamma + \delta_1 x_{ib}^E + \delta_2 D_t x_{ib}^E\right)$, which we expect to be between -1 and 0. A value of -1 means that equation (1) collapses to $p_{ict} = \alpha_{it} + \beta_{ct} + \epsilon_{ict}$, and therefore the price of any item can be decomposed into its national price (α_{it}), a common local market premium (β_{ct}), and an iid error term that is not persistent. In this case, any idiosyncratic price shock to a good in a city (ϵ_{ict}) has no impact on prices in the next period. Hence, price convergence occurs in one period, and prices always equal their conditional mean of ($\alpha_{it} + \beta_{ct}$) plus a random iid shock. At the other extreme, we have the case of where $\left(\gamma + \delta_1 x_{ib}^E + \delta_2 D_t x_{ib}^E\right) = 0$, which implies that the price of that good i in city c follows a random walk with a drift term given by $(\alpha_{it} + \beta_{ct})$. In intermediate cases where $\left(\gamma + \delta_1 x_{ib}^E + \delta_2 D_t x_{ib}^E\right) \in (-1, 0)$, prices converge across cities by price differences across cities can persist for more than k years.

We can write the approximate half-life of any price deviation from the steady-state price (measured in intervals of length k) as

$$H_t \equiv \frac{\ln(0.5)}{\ln\left(1+\hat{\gamma}+\hat{\delta}_1 x_{ib}^E+\hat{\delta}_2 D_t x_{ib}^E\right)}.$$

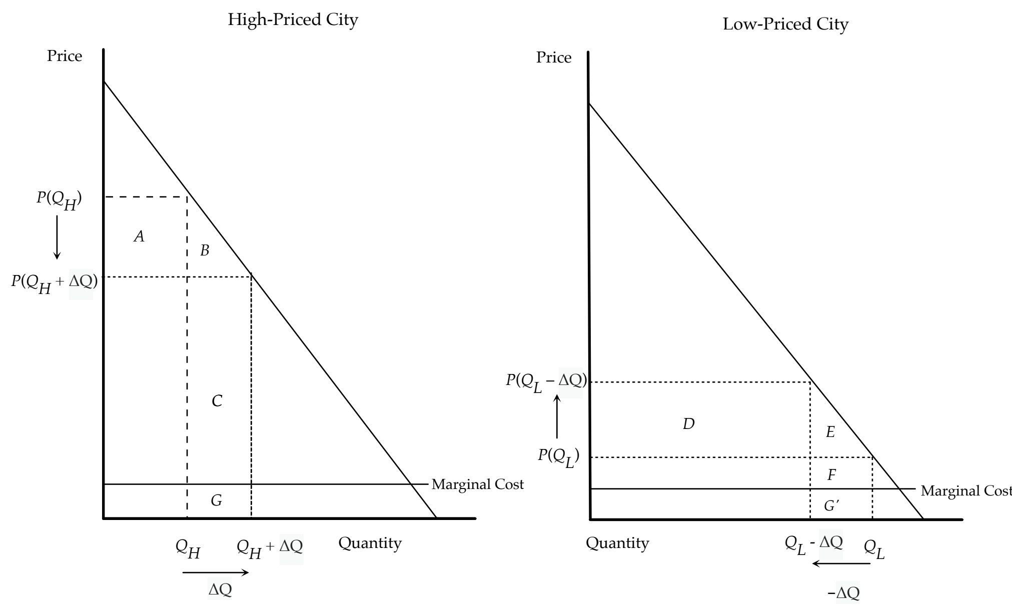
As one can see from the above formula, the change in the rate of convergence depends on all of the estimated convergence parameters; therefore there is not a simple mapping from changes in δ_t into rates of convergence.

2.2 Welfare in Partial Equilibrium

We can map the price changes into welfare gains by using the framework developed in Jensen (2007). Jensen considered a technological change that enabled arbitrage between a high-priced region (H) and a low-priced region (L). If e-commerce reduces price dispersion, we should expect the price in region H to fall and the price in L to rise as shown in Figure 1. Consumers in H will gain $(A+B)$, and sellers will gain $(C-A)$, yielding a net gain of $(B+C)$. Similarly, in region L, consumers will *lose* $(D+E)$ and sellers will gain $(D-F)$, yielding a net loss of $(E+F)$. Overall, the welfare gain is $(B+C)-(E+F)$, which will necessarily be positive in the case of linear demands with equal slopes as long as the price in H is at least as large as the price in the region L after arbitrage (i.e., $P(Q_H+\Delta Q) \geq P(Q_L-\Delta Q)$). One can also see this condition holds in the figure because both trapezoids $(B+C)$ and $(E+F)$ have identical bases and differ only in the heights of their parallel sides.

Jensen (2007) considered a case in which the marginal cost of supplying a good is zero, which enabled him to compute the lengths of the parallel sides of the quasi-trapezoids by just using the prices. When thinking about production more generally, however, marginal costs are likely to be positive, so technically we should subtract marginal costs from prices when computing the lengths of the parallel sides of the quasi-trapezoids. However, as one can see from Figure 1, if we assume constant and equal marginal costs of production, then $G = G'$, and we can still compute the

Figure 1: Welfare Gains from Arbitrage in the Jensen Model



welfare gain as $(B+C+G)-\left(E+F+G'\right)=(B+C)-(E+F)$.[1]

We can use our estimates of the impact of e-commerce on price convergence to calibrate the Jensen model. In order to compute the partial equilibrium welfare gain due to e-commerce, we consider the difference in implied gains in two counterfactual cases. In each case, we will assume that the economy has deviated from a steady state equilibrium but experiences different rates of price convergence. The first case corresponds to one in which consumers do not have access to e-commerce, so price convergence is slow, which results in small movements towards a common price. The second case is one in which consumers do have access, which results in greater price convergence and therefore greater welfare gains. We then set the welfare gain associated with e-commerce to be equal to the difference in the welfare gains arising from the different convergence rates.

Let D denote each counterfactual case, where $D=0$ corresponds

[1]The assumption of equal marginal costs is probably not extreme for Japan given the small physical size of the country (most major cities are within a few hours drive of Tokyo), which means that transport costs are unlikely to produce large price differences across cities.

to a counterfactual with no e-commerce and $D = 1$ corresponds to a counterfactual with e-commerce. We will consider a counterfactual in which observed prices constitute deviations from a free-trade steady state in which goods prices are the same in all cities $p^*_{ic} = p^*_i$. One of the features of thinking about convergence to toward this free-trade steady state is that we will show that there will always exist a p^*_i such that price convergence towards that level will result in no net increase in demand as in Jensen (2007). and do not vary across time, i.e., , A necessary condition for steady-state prices (p^*_{ic}) is $\Delta p^*_{ic} = 0 = \alpha_{it} + \beta_{ct} + \left(\gamma + \delta_1 x^E_{ib} + \delta_2 D_t x^E_{ib}\right) p^*_i$

$$\Delta p^*_{ic} = 0 = \alpha_{it} + \beta_{ct} + \left(\gamma + \delta_1 x^E_{ib} + \delta_2 D_t x^E_{ib}\right) p^*_i. \tag{2}$$

Since the last term in this equation does not vary with t or c, it must be the case that in the free-trade steady state, $\alpha_{it} + \beta_{ct} = \alpha^*_i$. This condition intuitively implies that in the steady state α_{it} and β_{ct} cannot vary with time, so $\alpha_{it} = \alpha_i$ and $\beta_{ct} = \beta_{c't} = \beta^*$. Thus, we can rewrite this equation as

$$0 = \alpha^*_i + \beta^* + \left(\gamma + \delta_1 x^E_{ib} + \delta_2 D_t x^E_{ib}\right) p^*_i. \tag{3}$$

Suppose that we start in this steady state and perturb steady-state prices (p^*_i) in period $T-1$ to some other values, $p_{ic,T-1}$. In period T, we will observe prices change by $\widehat{\Delta p}_{icT}(D) = \alpha^*_i + \beta^* + \left(\gamma + \delta_1 x^E_{ib} + \delta_2 D_t x^E_{ib}\right) p_{ic,T-1}$. If we subtract equation (3) from this equation we obtain

$$\widehat{\Delta p}_{icT}(D) = \left(\gamma + \delta_1 x^E_{ib} + \delta_2 D_t x^E_{ib}\right)\left(p_{ic,T-1} - p^*_i\right). \tag{4}$$

Using the log change as an approximation for the percentage change, the price level in period T, $P_{icT}(D)$, can be written as $P_{icT}(D) = P_{ic,T-1}\left[1 + \widehat{\Delta p}_{icT}(D)\right]$. If we assume a constant elasticity of substitution (CES) demand system, the demand for good i in city c in time t in counterfactual D is given by

$$Q_{ict}(D) = \frac{\left(P_{ict}(D)/\varphi_{ic}\right)^{-\sigma}}{\left[P_{ct}(D)\right]^{1-\sigma}} E_c, \text{ where } P_{ct}(D) \equiv \left[\sum_i \left[\frac{P_{ict}(D)}{\varphi_{ic}}\right]^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \tag{5}$$

where σ is the demand elasticity. It will also be useful to denote the log change in the city price index by $\Delta p_{ct} = \ln\left[P_{ct}\left(D\right)/P_{c,t-1}\right]$.

Following Jensen, we consider a set of price changes that are consistent with equation (4) that imply no aggregate quantity changes, i.e., $\Delta Q_{iT}\left(D\right) = \sum_c \Delta Q_{icT}\left(D\right) = 0$. Equation (5) implies that

$$\Delta q_{icT}\left(D\right) = \left(\sigma - 1\right)\Delta p_{cT}\left(D\right) - \sigma\widehat{\Delta p}_{icT}\left(D\right) + \Delta \ln E_{cT},$$

If we make the partial equilibrium assumption that aggregate prices and urban expenditures are unchanged, this equation reduces to

$$\Delta q_{icT}\left(D\right) = -\sigma\widehat{\Delta p}_{icT}\left(D\right). \tag{6}$$

Using the log change as an approximation for the percentage change, the counterfactual change in urban consumption in any city c in time T can be written as $\Delta Q_{icT}\left(D\right) = Q_{ic,T-1}\Delta q_{icT}\left(D\right)$. Substituting equation (6) into this equation and summing produces

$$\sum_c Q_{ic,T-1}\widehat{\Delta p}_{icT}\left(D\right) = 0, \tag{7}$$

where we have made use of the assumption in Jensen (2007) that price arbitrage does not produce aggregate changes in quantities, so $\Delta Q_{iT}\left(D\right) = 0$. If we then substitute equation (4) into equation (7), we obtain

$$\sum_c Q_{ic,T-1}\left(\gamma + \delta_1 x_{ib}^E + \delta_2 D_t x_{ib}^E\right)\left(p_{ic,T-1} - p_i^*\right) = 0,$$

which means that the steady-state price for each good is given by

$$p_i^* = \frac{\sum_c Q_{ic,T-1}\left(\gamma + \delta_1 x_{ib}^E + \delta_2 D_t x_{ib}^E\right) p_{ic,T-1}}{\sum_c Q_{ic,T-1}\left(\gamma + \delta_1 x_{ib}^E + \delta_2 D_t x_{ib}^E\right)}. \tag{8}$$

The partial equilibrium welfare gain arising from prices moving from their values in $T-1 \quad (P_{icT-1})$ towards their steady state values (P_i^*) can be written as

$$\Delta W_{icT} = \frac{1}{2}\left(2P_{icT-1} + \Delta P_{icT}\left(D\right)\right)\Delta Q_{icT}\left(D\right) - m_i \Delta Q_{icT}\left(D\right),$$

where m_i is the marginal cost of producing the good. This welfare gain will be positive whenever prices are higher than their steady-state levels and negative otherwise.

The national welfare change associated with a price convergence toward steady states price levels equals

$$\Delta W_{iT}(D) = \frac{1}{2}\sum_c \left(2P_{icT-1} + \Delta P_{icT}(D)\right)\Delta Q_{icT}(D) - \underbrace{m_i \sum_c \Delta Q_{icT}(D)}_{=0}.$$

The welfare gain in the economy expressed as a share of national expenditures, E_T, is

$$\Delta W_T(D) = \sum_i \frac{\Delta W_{iT}(D)}{E_{T-1}(D)}.$$

The gain due to e-commerce is simply the difference between the welfare gain obtained from price arbitrage in the e-commerce regime less that obtained in the regime without e-commerce or

$$\Delta W_T = \Delta W_T(D=1) - \Delta W_T(D=0). \tag{9}$$

3 Data

One reason Japanese data is useful for testing the theory because e-commerce expanded rapidly in Japan, which allows us to break the time series into pre- and post-e-commerce periods. Moreover, the share of e-commerce retail transactions in Japan are similar to those in the U.S.[2] By April of 2000, when Japan's largest e-commerce firm, Rakuten, announced its initial public offering, it had grown to be a platform in which consumers had access to goods available from 2,300 merchants, and the Rakuten

[2]Japan's Ministry of Economy Trade and Industry reports that 5.8% of all retail transactions were done online in 2017, roughly the level seen in the U.S. in 2014. See http://www.meti.go.jp/english/press/2018/0425_002.html and https://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf. While we do not know when each city obtained broadband internet, we do know that every prefecture in Japan had digital subscriber lines (DSL) and cable TV connections available by 2001, and about a quarter of all households were subscribing to DSL by the end of 2004. In addition, many consumers also used cell phones to make purchases. Source: Ministry of Public Management, Home Affairs, Posts and Telecommunications (https://www.stat.go.jp/english/data/handbook/pdf/2018all.pdf#page=23). We thank Takashi Unayama for providing us with these numbers.

website was getting 95 million hits per month—almost one hit for every man, woman, and child in Japan.[3] The following year sales on the Rakuten platform exceeded ¥52 billion (about $430 million). Thus, within five years, Japanese consumers in any city went from only being able to buy locally or from catalogs to being able to purchase goods from thousands of merchants located across Japan. Rakuten's growth was part of a broader e-commerce boom in Japan. Amazon entered the Japanese market in 2001, with Rakuten still accounting for 30% of Japanese e-commerce transactions in 2010.[4] By 2017, e-commerce firms accounted for 5.8 percent of Japanese retail sales or about ¥16.5 trillion (about $149 billion).

A major advantage of Japanese data is that one can obtain measures of consumer expenditures by product and retail outlet. The National Survey of Family Income and Expenditures (NSFIE) is a representative survey of households with two or more members that reports expenditures by retail outlet type for the same product categories as the ones used in the Family Income and Expenditure Survey (FIES) to construct the Japanese CPI.[5] Starting in 2004, the NSFIE also began a quinquennial recording the expenditure share of each product from online merchants.

One of the problems with the NSFIE data is that it tends to under-report aggregate internet sales because mixed-method retailing (e.g., seeing a product in a store and buying it online tends to be placed in the "other" category). Fortunately, the Ministry of Economy Trade and Industry (METI) reports very reliable aggregate estimates of sales by e-commerce and other retailers by surveying actual sales to consumers by retail merchants. We therefore scale the NSFIE data by the ratio of aggregate sales in the METI data relative to the NSFIE data in order to obtain the same value for aggregate e-commerce sales in the two datasets. In order to make sure that sampling problems are not driving our results, we will use catalog sales as

[3]Phred Dvorak, "Japan's Highly Popular Rakuten Plans IPO Despite Shaky Market," *Wall Street Journal*, April 18, 2000.

[4]Rakuten, Inc. (2010) *Annual Report.*

[5]The retail outlet types are small retail, supermarket, convenience, department, club, discount, catalog, internet, and "other".

an instrument to deal with classical measurement error and also conduct a robustness check for all of our main results using data from Rakuten.

We construct a measure of the e-commerce sales intensity for each of the CPI expenditure categories by computing the share of online expenditures in total expenditures. To do this, let e_{ib} denote the average household total expenditures in category i in survey year ($b \in \{1999, 2004, 2009, 2014\}$. We denote expenditures in category i from retail channel r in survey year b by s^r_{ib}. We let r take on three values (*E*, *C*, and *R*) corresponding to whether we are measuring expenditures incurred through any one of three retail channels: e-commerce, catalog, or the Rakuten platform. We then define the retail channel "intensity" x^r_{ib} of category i by dividing the expenditures through retail channel r by total expenditures (e_{ib}), normalized by the maximum value of this ratio, i.e.,

$$x^r_{ib} = \frac{s^r_{ib}}{e_{ib}} / \max_j \left(\frac{s^r_{jb}}{e_{jb}} \right). \tag{10}$$

Thus, our measure of the expenditure intensity of retail channel r equals zero if there are no expenditures on goods via a retail channel r in expenditure category i and a value of 1 if the expenditure through retail channel r relative to that in the economy is the highest among all categories of goods sold through that retail channel. Expressing retail channel intensity this way makes our intensity variable (x^r_{ib}) invariant to the size of sector i.

In order to see how retail intensity varies across products, we aggregated the FIES product categories into broader ones in Table 1 so that we could display the data in a compact form. The rows are ordered by a category's share of Japanese expenditures on goods. The first column of Table 1 reports the percentage of expenditures in category ℓ among goods in 2009 as reported in the FIES ($E_{\ell b} \equiv \sum_{i \in \Omega^\ell} e_{ib} / \sum_j e_{jb} \times 100$), where Ω^ℓ is the set of items in some more aggregated category ℓ. In the second column, we report the percentage of online expenditure in 2009 that corresponds to that category ($S^E_{\ell b} \equiv \sum_{i \in \Omega^\ell} s^E_{ib} / \sum_j s^E_{jb} \times 100$), where s^E_{ib} is online expenditure from NSFIE). Columns 3-5 report the e-commerce intensity (i.e., $x_{\ell b}^{E} \equiv S_{\ell b}^{E}/E_{\ell b}/\left[\max_k \left\{S_{kb}^{E}/E_{kb}\right\}\right])$.

Table 1 makes clear some basic stylized facts of our data. First, there is enormous variation in the e-commerce intensity. Some of this reflects the fact that highly perishable, non-standardized items (e.g. fresh foods), restricted/time-sensitive items (e.g., medicine and physical newspapers), and high weight-to-value items (non-perishable groceries) are not sold much online. At the other end of the spectrum, we see that more standardized goods—e.g., electronics, books, clothing, footwear, and furniture and furnishings—are sold very intensively online. Interestingly, we see that domestic utensils, household consumables (which includes non-durable household supplies like paper products and cleaning agents), and recreational goods (which includes items like sports equipment and gardening supplies) are sold very intensively online as well. Second, if we compare the values for 2004, 2009, and 2014, we see a lot of persistence in what is sold online. Newspapers, meat, dairy products, and fruit and vegetables were not sold much online in 2004 and have low e-commerce sales intensity in all subsequent years. Similarly, electronics has the highest internet sales intensity in all of the survey years. Third, as one can see in the second-to-last column, Rakuten sales intensity is highly correlated with e-commerce sales in the NSFIE data ($\rho = 0.57$), which suggests that these datasets are in broad agreement as to what goods are sold intensively online.

One of the other striking features of the table is that if we compare catalog sales intensity (column 7) with e-commerce intensity (columns 3-6), we see that there is a lot of similarity between goods that are sold intensively online and goods that were sold intensively by catalogs in 1999. In that year, e-commerce firms in Japan were still in their infancy: Amazon had not yet entered the Japanese market and Rakuten only had 5.5 million dollars worth of sales on its platform (Olson (2012)). Thus, we can be fairly confident that Japanese catalog sales were probably not much influenced by e-commerce sales. Nevertheless, it is clear that goods sold intensively online tend to

Table 1: E-Commerce intensity of consumer expenditure on goods

Category	Share Expenditure 2009		E-Commerce Intensity				Catalog Intensity
	Total	E-Commerce	2004	2009	2014	Rakuten 2010	1999
Fruits and vegetables	10.24	1.76	0.01	0.03	0.05	0.03	0.06
Household consumables	10.19	18.00	0.15	0.36	0.28	0.58	0.34
Clothing	9.61	13.45	0.11	0.28	0.22	0.42	0.41
Store-bought cooked food	7.62	1.10	0.03	0.03	0.04	0.03	0.04
Cereal	6.21	1.54	0.02	0.05	0.05	0.07	0.06
Fish and shellfish	6.13	1.40	0.02	0.05	0.05	0.04	0.05
Cakes and candies	5.72	1.62	0.03	0.06	0.04	0.08	0.05
Meat	5.55	0.73	0.01	0.03	0.04	0.03	0.02
Recreational goods	4.65	12.71	0.30	0.55	0.47	0.93	0.22
Household applicances	4.05	6.32	0.21	0.31	0.36	0.35	0.17
Electronics	3.88	19.32	1.00	1.00	1.00	0.53	0.41
Alcoholic beverages	3.36	1.32	0.05	0.08	0.10	0.26	0.06
Medicine and nutritional supplements	3.35	4.85	0.23	0.29	0.31	0.23	1.00
Non-alcoholic beverages	3.17	2.20	0.09	0.14	0.15	0.16	0.27
Oils, fats and seasonings	3.11	0.73	0.02	0.05	0.07	0.05	0.09
Newspapers and magazines	2.96	0.00	0.00	0.00	0.00	0.00	0.00
Dairy products and eggs	2.81	0.29	0.01	0.02	0.04	0.01	0.02
Transportation equiment	2.14	3.01	0.23	0.28	0.18	0.58	0.40
Domestic utensils	2.06	4.04	0.14	0.39	0.49	0.53	0.41
Furniture and furnishings	1.78	3.45	0.33	0.39	0.51	1.00	0.56
Footwear	1.40	2.13	0.14	0.30	0.28	0.92	0.33
Total/Mean	100.00	100.00	0.15	0.22	0.23	0.32	0.24

Note: Shares are expressed as percentages. This table shows the share of consumption expenditure, e-commerce expenditure, and e-commerce sales intensity, and catalog intensity for goods. E-Commerce intensity and catalog intensity are defined in equation (10).

have characteristics that are similar to those goods historically available in catalogs, which will motivate our instrument.

In addition to the retail sales data that we have been discussing, we also make use of the fact that the Japan Statistical Bureau (JSB), which produces the Japanese CPI, provides detailed information on representative prices of the products in the FIES categories. These prices are sampled in 165 cities on average, which gives us the ability to not only tracking product prices across time but also across space. This information identifies the brand of an item or provides a detailed description (e.g., "Big-eyed tuna, sliced (for sashimi), lean, 100g"). Since an objective of the JSB sampling is to make meaningful intercity price comparisons, tries to select products available in all cities.[6]Finally, we use the official quality-adjusted price quotes for Tokyo computed by the JSB in order to adjust the prices in other cities when goods are substituted into and out of the sample.[7]

Table 2 reports the sample statistics for our data. The first three lines of the table report the measure of e-commerce intensity (x^E_{ib}) computed for each of the survey years $b = \{2004, 2009, 2014\}$. These summary statistics

[6]One potential concern with these data is that the JSB may not be sampling the same goods in different cities, so unlike barcode data in which goods are precisely defined, some of the price variation in our sample may be capturing unmeasured quality variation instead. Since Hottman, Redding, and Weinstein (2016) show that the correlation between price and quality in bar-code data is 0.9, so we should expect sampling problems to produce greater levels of price dispersion in JSB data is likely to be larger than that in barcode data because variation in JSB data would be capturing both price and quality variation. In order to check for this, we compute the log relative price of each good in each city ($\tilde{p}_{ict} = p_{ict} - \frac{1}{C}\sum_c p_{ict}$) and take the standard deviation of $\tilde{p}_{ict}$. When we do this, we find that the standard deviation of intercity price differences for the same good in Japan is 17 percent. By contrast, Broda and Weinstein (2008) find the standard deviation in intercity prices of bar-coded goods is 22 percent in the US and 19 percent for Canadian provinces. The fact that intercity price dispersion of goods in the Japanese CPI is lower than that for bar-coded goods in the US and Canada suggests that the JSB item definitions probably do not include goods that differ substantially in quality in different cities and therefore that quality variation across cities for the same product is unlikely to be a major problem in our data. In order to further reduce the impact of measurement error, we also trimmed 3 smallest and 3 largest price quotes within an item-year observation and dropped the bottom and top 1% of log price changes.

[7]Source: http://www.e-stat.go.jp/SG1/estat/List.do?bid=000001033703&cycode=0, accessed on April 5th, 2017.

highlight the skewness in the distribution of e-retail sales intensity that we saw in Table 1. Some goods are sold very intensively online, but most goods are purchased predominantly in physical stores. Looking at the value of e-commerce intensity in the middle of the period (x^E_{i09}), we see that goods in the the upper 90^{th} percentile of the distribution have an e-commerce sales intensity of 0.19 over the full sample period, which is more than eight times higher than a good with the median intensity. We also can see that there are substantial increases in e-commerce intensity at the 50^{th} and 90^{th} percentiles, which reflects the growing importance of e-commerce across the set of goods in the sample. The fourth line of the table recomputes e-commerce intensity using the data from Rakuten (x^R_{i10}). The values of x^E_{i09} and x^R_{i10} are quite similar, indicating that both datasets indicate similar distributions of the e-commerce intensity. The fifth line of Table 2 presents catalog sales intensity in 1999, which has a similar distribution as e-commerce intensity, especially in the later years. Finally, the last row shows the annual growth rate of prices from 1991 to 2016. Ninety percent of annual product price changes in cities were less than 11 percent in absolute value, with the typical price change being close to zero.

Table 2: Summary Statistics

	N	Mean	St. Dev.	Min	p10	p50	p90	Max
x^E_{i04}	321	0.043	0.095	0.000	0.000	0.011	0.091	1.000
x^E_{i09}	325	0.070	0.111	0.000	0.000	0.022	0.193	1.000
x^E_{i14}	324	0.103	0.143	0.000	0.016	0.037	0.280	1.000
x^R_{i10}	540	0.073	0.119	0.000	0.001	0.025	0.182	1.000
x^C_{i99}	327	0.074	0.111	0.000	0.001	0.029	0.217	1.000
Δp_{ict}	791,608	-0.001	0.112	-1.798	-0.114	0.000	0.110	1.679

Note: This table shows summary statistics of e-commerce intensity, catalog intensity, and annual price growth rates from 1991 to 2016; x^E_{i04}, x^E_{i09}, and x^E_{i09} denote e-commerce intensity in 2004, 2009, and 2014, respectively; x^R_{i10} is e-commerce intensity using Rakuten sales data in 2010; x^C_{i99} denotes catalog intensity in 1999, where these variables are defined in equation (10). Prices are in natural log. Δp_{ict} is the one-year log difference in prices.

4 Results

We present our results in three sections. Section 4.1 shows how e-commerce has affected national prices. In Section 4.2, we present plots to show that price convergence is a central tendency in the data and that the internet appears to have changed the rate of convergence for goods available online but not for other goods. This provides some *prima facie* evidence that our focus on relative intercity price movements of goods sold by e-retailers as opposed to absolute price declines of online goods is in line with the data. We next estimate the impact of e-retail on the rate of price convergence and we present our estimates of the welfare gain from e-retail. Finally, in Section 4.3, we show welfare gains in new trade models.

4.1 E-commerce and National Prices

Goolsbee and Klenow (2018) found that goods traded online have inflation rates that were about 1.3 percentage point lower than goods in the same product categories in the CPI. Here, we present that goods traded online have lower price increase rates than goods not available online. We also find that differential rates of price increase were present long before the entry of e-commerce firms, became more pronounced after the entry of e-commerce merchants, and arose in part because the rate of price increase of goods not available online rose. In order to examine this in the data, we regress annual log price changes of goods (Δp_{ict}) on good (α_i) fixed effects along with an indicator variable, D_t, that is one starting in 1997 (the year Rakuten opened) and zero before as well as the e-commerce intensity of the good interacted with this dummy ($x^E_{i09}D_t$):

$$\Delta p_{ict} = \alpha_i + \phi D_t + \theta x^E_{i09} D_t + \epsilon_{ict}, \tag{11}$$

where α_i is a parameter to capture any pre-trends in the data that might arise if goods available online exhibit have different price increase trends than goods not available online. The coefficient on D_t (ϕ) tells us whether there was any differential trend in price increase for goods available online after the entrance of e-commerce firms and θ, the coefficient on the e-commerce intensity interaction term ($x^E_{i09} D_t$), tells us about the differential rate of price change for goods traded online after the entry of e-commerce firms.

One of the advantages of our specification is that we can eliminate any good-specific pre-trends (α_i) that might confound specifications that compare price growth rates of goods available online with those not sold online. In order to understand whether controlling for these pre-trends is likely to be important, we split the sample into two groups by e-commerce sales intensity. The first sample of goods (X_B) consists of products that have an e-commerce sales intensity (x^E_{i09}) in the bottom quartile, and second sample is composed of goods with an e-commerce sales intensity in the top quartile (X_T). We then computed the average rate of price increase for the two sets of goods by running the following regression separately for each sample:

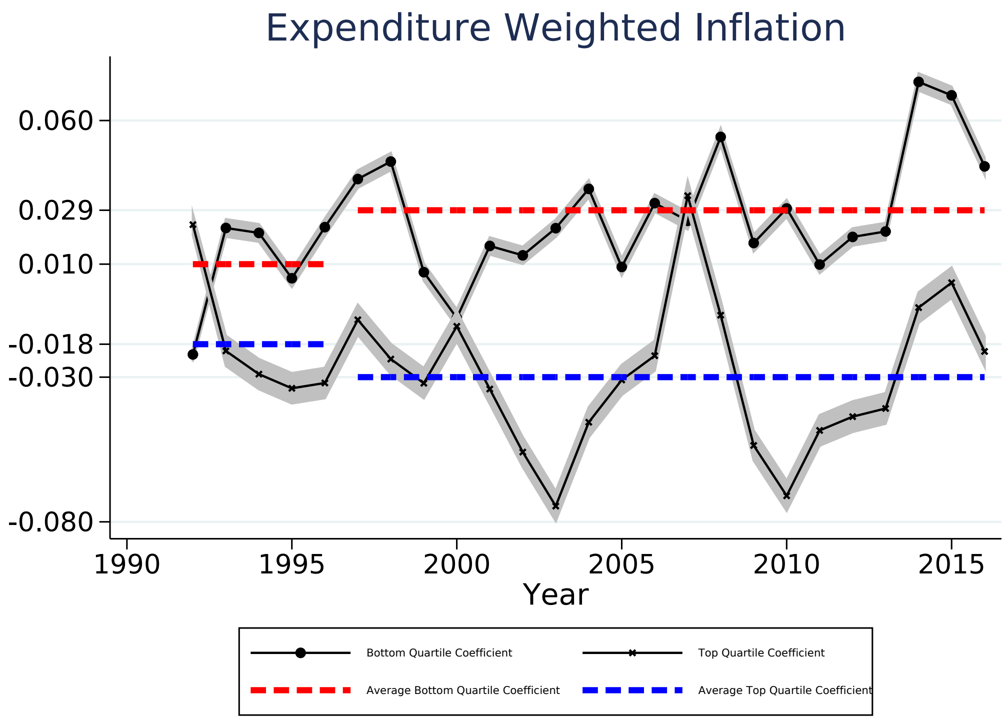
$$\Delta p_{ict} = \theta_t + \epsilon_{ict}, \tag{12}$$

where the estimates of the time fixed effect θ_t in each sample tell us the average rate of price increase for the goods in each sample.

We plot these expenditure-weighted estimates and the 95-percent confidence bands in Figure 2. As the figure makes clear, there are unmistakable pre-trends in the data.[8] Before the entry of the Rakuten in 1997, the average rate of price increase for the types of goods that would ultimately be sold on e-commerce platforms was -2.0 percent per year, while the average annual rate of price increase for goods that not sold much on these platforms was 1.0 percent per year. Thus, even before the entry of e-commerce firms, there was a 3 percentage point gap between the relative rates of price increase for goods that would be sold intensively online relative to those never sold intensively online. These differences in rates of price increase may reflect the fact that the production of

[8] In online appendix Figure A.2, we also present unweighted estimates, which show a similar pattern. The relatively low bottom-quartile point estimate for 1992 is driven by fruits and vegetable prices in 1992 as can be seen by looking at online appendix Figure A.1. When we drop fruits and vegetables, which have very volatile price movements in Japan, the rates of price change of goods in the bottom and top quartiles look quite similar in 1992.

Figure 2: Price Growth of Goods with High and Low E-Commerce Intensity



Note: Black lines show the average rate of expenditure-weighted price increase for the goods in two groups: products with bottom quartile e-commerce sales intensity (black line with dots) and products with top quartile e-commerce intensity (black line with x's). Shaded areas show the 95-percent confidence bands. The red dashed line shows the average rate of price increase before and after the entry of e-commerce firms for goods with bottom quartile e-commerce sales intensity and the blue dashed line shows that for goods with top quartile e-commerce sales intensity.

standardized, non-perishable goods, which tend to dominate e-commerce platforms, may benefit more from the cost reductions associated with modern manufacturing techniques.

It is also interesting to see what happened to this gap in rates of price change after the entry of e-commerce firms. While we do not see much change in pricing behavior in the first five years after the entry of Rakuten, by 2002, we see that the differences in the price growth rates between the two sets of goods widened significantly in subsequent years, when e-commerce firms became major players in Japanese retail. Goods in the top quartile of e-commerce sales intensity had an average rate of price growth from 1997 to 2016 of -3.5 percent per year: a 1.5 percent per year fall in the rate of price growth. By contrast, the rate of price growth for goods in the bottom quartile of e-commerce sales *rose* to 2.9 percent per year: an increase of 1.9 percent per year.

Table 3: Relative Price Changes and E-Commerce Intensity

	(1)	(2)	(3)	(4)
	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}
D_t	-0.0015	0.0094	-0.0036	0.0107
	(0.0024)	(0.0023)	(0.0035)	(0.0030)
E-Commerce Intensity	0.0038	-0.0912	0.0457	-0.1158
$\times D_t$	(0.0251)	(0.0209)	(0.0601)	(0.0384)
Sample	Goods	Goods	Goods	Goods
Fixed Effects	Product	Product	Product	Product
Estimation Period	1992-2001	1992-2016	1992-2001	1992-2016
Observations	272,469	581,708	272,469	581,708
R^2	0.03	0.03		
First-Stage F-Stat			27.20	30.26
Estimation Method	OLS	OLS	IV	IV

Note: The dependent variable is the one-year log price change; D_t is dummy variable that is one after 1996 (i.e., the post e-commerce period); and e-commerce intensity (x^E_{i09}) is defined in equation (10). Table shows relative price changes for goods sold online intensively relative to goods not sold online intensively before and after the entry of e-commerce firms. Column 1 and 3 are for 1992-2001 and column 2 and 4 are for 1992-2016. The first two columns show ordinary least-squares (OLS) estimates using e-commerce sales intensity and the second two columns use catalog sales intensity as IV. Standard errors in parentheses.

Turning to our differences-in-differences specification, we present the results from estimating equation (11) in Table 3. The first column presents the results from estimating equation (11) over the period 1992 to 2001. Consistent with what we observed in Figure 2, we do not find much of an effect from e-commerce in the first few years after the entry of Rakuten. However, as one can see in column 2, we do see a significant decline in the *relative* prices of goods available online as evidenced by the coefficient of -0.09 on the post-e-commerce e-commerce intensity interaction ($x^E_{i09}D_t$) term.

As we have argued earlier, one possible challenge to our identification strategy is that e-commerce firms are not likely to have chosen which sectors they are likely to have entered randomly. In order to deal with this endogeneity, we use catalog intensity (x^C_{i99}) as an instrument for e-commerce intensity (x^E_{i99}). Table 4 shows the strength of catalog sales intensity as an instrument for e-commerce intensity. As one can see from the *F*-statistic reported in the first two columns of the table, catalog sales intensity in 1999 is a strong instrument for e-commerce sales intensity in 2009. Sectors that on average were major channels for catalog sales also became major channels of e-commerce firms. In the third, column we simply regress the e-commerce intensity of sectors in 2009 on catalog intensity in 1999 to show that the relationship holds in the cross section.

We report the results from our instrumental variables (IV) estimation in columns 3-4 of Table 3. As before, we do not see much of an effect of e-commerce on national pricing in the first few years after the entry of Rakuten and the other e-commerce firms, but we do see strong effects in subsequent years. Overall, our IV estimate of the impact of e-commerce intensity ($x^E_{i09}D_t$) on price increases is about 20 percent larger in magnitude than the OLS estimate in the full sample estimates (columns 2 and 4) but the difference is not significant. The fact that the OLS estimates are attenuated implies that e-commerce firms tended to enter sectors where prices were rising, perhaps because these markets were likely to be more profitable. This pattern of behavior would explain why estimates that do not control for the endogeneity of market entry tend to underestimate the the relative impact of e-commerce on pricing. It is also consistent with our e-commerce variable not exhibiting much measurement error, which would also produce an attenuation bias in the OLS results. In terms of economic significance, the results in column 4 imply that a good at the 90^{th} percentile of internet sales intensity had rates of price increase that were 3.3 percentage points per year lower than goods not sold online after the entry of e-commerce firms.

Table 4: First Stage of Instrumental Variables Regression

	(1) E-Commerce Intensity $\times D_t$	(2) E-Commerce Intensity $\times D_t$	(3) E-Commerce Intensity
Catalog Intensity $\times D_t$	0.2899	0.2912	
	(0.0556)	(0.0529)	
D_t	0.0304	0.0318	
	(0.0044)	(0.0044)	
Catalog Intensity			0.2622
			(0.0144)
Constant			0.0442
			(0.0022)
Sample	Goods	Goods	Goods
Fixed Effects	Product	Product	None
Estimation Period	1992-2001	1992-2016	
Observations	272,469	581,708	1,639
R^2	0.23	0.22	0.17
First-Stage F-Stat	27.20	30.26	
Estimation Method	IV-First Stage	IV-First Stage	OLS

Note: E-Commerce intensity (x^E_{i09}) and catalog intensity (x^C_{i99}) are defined in equation (10); D_t is dummy variable that is one after 1996 (i.e., the post e-commerce period). The first two columns of the table present the first-stage regression results (i.e., separate observations for each city and year): column 1 shows results using data for 1992-2001, and column 2 uses data for 1992-2016. The last column presents an OLS regression using only the goods data for 2009. Standard errors in parentheses.

4.2 Gains Due to Price Arbitrage

As the last section made clear, while there is strong evidence that the rise of e-commerce caused the relative prices of goods sold online to decline in Japan, we cannot interpret this as indicating that the overall price level to fell because the lower relative rate of price increase for goods sold intensively by e-commerce firms was in part due to higher rates of price increase for goods sold principally by physical merchants. In this section, we explore an alternative mechanism through which e-commerce affected prices in Japan: reducing price dispersion across cities.

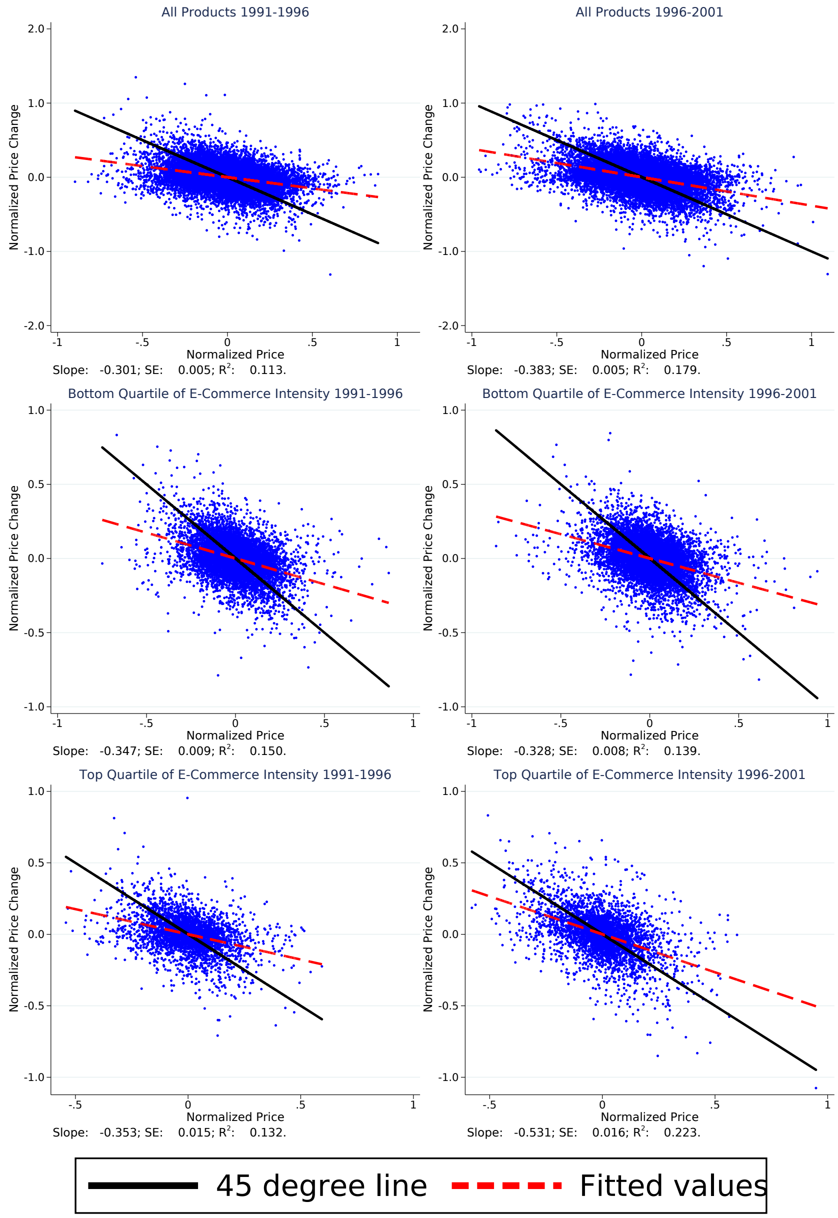
We consider two five-year periods: the first period (1991-1996) predates e-commerce and the second one (1997-2001) ends after Rakuten was a prominent, listed company, with tens of millions of hits and thousands of stores selling on its platform. It is difficult to compare price changes across goods and cities in their raw form because rates of price change vary across goods and cities. We therefore normalize the data by regressing Δp_{ict} and p_{ict} on product and city fixed effects and construct normalized price changes ($\Delta^5 p_{ict} - \hat{\alpha}_{it} - \hat{\beta}_{ct}$) and normalized price levels ($p_{ic,t-5} - \hat{\alpha}'_{it-5} - \hat{\beta}'_{ct-5}$), where $\hat{\alpha}_{it}$ ($\hat{\alpha}'_{it-5}$) and $\hat{\beta}_{ct}$ ($\hat{\beta}'_{ct-5}$) are the estimated fixed effects from the regression of Δp_{ict} (p_{ict-5}) on product and city fixed effects. Thus, these normalized prices remove the effect of any common price movements at the product or city level. Figure 3 presents plots of normalized five-year change in prices ($\Delta^5 p_{ict} - \hat{\alpha}_{it} - \hat{\beta}_{ct}$) against the normalized five-year lag of prices in each city ($p_{ic,t-5} - \hat{\alpha}'_{it-5} - \hat{\beta}'_{ct-5}$).

The top panel shows how normalized price changes vary with normalized prices before and after the entry of e-commerce. There is a clear negative relationship between initial urban price deviations and future price growth, which indicates that goods that had high prices in cities tend to have lower rates of price increase than goods with low relative prices. This mean reversion is likely the product of price arbitrage. As one can see from these two plots, 30 percent of any relative price difference tends to be eliminated within five years before the advent of e-commerce and this number rose to 38 percent in the five years after e-commerce firms entered. These plots also speak to the relatively high quality of the Japanese data. For example, studies using U.S. data (c.f., Parsley and Wei (1996)) find no evidence of price convergence once one controls for city fixed effects.[9]

The next two pictures show what is driving this increase in the intercity rate of price convergence. Here, we divide the sample into the set of

[9] One plausible reason for the weaker evidence of price convergence in the U.S. is that that the data used in Parsley and Wei (1996) is not based on purposive sampling, so price changes in cities are based on a changing mix goods of different qualities across locations (as shown in Handbury and Weinstein (2015)).

Figure 3: Normalized Price Change vs. Normalized Price



Note: This graph plots normalized price changes against normalized price levels. Normalized price changes (levels) equal the actual price changes (levels) less the fixed effects from a regression of price changes (levels) on product and city fixed effects. The left panel shows normalized price changes before the entry of e-commerce and the right panel shows them after the entry of e-commerce. The top panel plots for all goods, the middle panel plots for goods with e-commerce intensity lower than the bottom quartile, and the bottom panel shows for goods with e-commerce intensity higher than the top quartile.

goods with an internet sales intensity in the lowest first quartile of the distribution in 2009 ($x^E_{i09} < 0.014$) and the set of goods in the highest quartile of the distribution ($x^E_{i09} > 0.117$). As one can see from the middle panel in Figure 3, there was almost no change in the rate of convergence for goods not sold on the e-commerce. The slope of the line for goods not sold intensively online in the early period is -0.35, which is almost identical to the slope in the post e-commerce period (-0.33). In other words, the entry of e-commerce firms seems not to have affected the speed at which intercity price differentials converged for goods not sold intensively online. However, we see a very different pattern for goods with an e-commerce intensity in the upper quartile of the distribution. The slope steepens by 56 percent, rising in magnitude from -0.35 to -0.55. Thus, enabling consumers to shop online seems to have significantly reduced the ability of merchants to charge different prices in different cities for the same good. We now turn to exploring this result rigorously.

4.2.1 Estimating Convergence Rates

Following Rogoff (1996), we can test for whether we observe absolute price convergence or relative price convergence by estimating equation (1) and seeing whether the estimated city-time fixed effects are jointly zero. If they are, then the data suggests that the prices of goods are converging to the same price across cities. Otherwise, it implies that the prices of goods converge to different levels in different cities. We can use an *F*-test to reject the hypothesis that the city-year fixed effects are zero, which suggests that absolute price convergence fails, so average price levels of goods do not converge to exactly the same level in all cities. We therefore include city-time fixed effects in our specifications.

Table 5 presents the results of estimating equation (1) for five- and one-year intervals using 1999 catalog sales intensity as an instrument for e-commerce sales intensity. In the first two columns, we present separate regressions for 1996 and 2001, where we let the convergence rates vary across the two time periods as we did in the earlier plots. Comparing the first rows of columns 1 and 2 reveals the convergence rates for goods not suitable for e-commerce (i.e., those where $x^E_{i09} = 0$) were almost identical before and after the entry of e-commerce, which is the result that we saw in Figure 3. The coefficient on e-commerce intensity interacted with lagged prices ($x^E_{i09} p_{ic,t-5}$) in column 1 indicates that the rate of convergence for goods suitable for e-commerce sales was not significantly different than the convergence rate of other goods prior to to the entry of e-commerce. However, the negative and significant coefficient on the triple interaction term ($D_t x^E_{i09} p_{ic,t-5}$) in the post-e-commerce sample indicates that goods sold intensively online exhibit significantly faster convergence rates after the entry of e-commerce firms, which formally confirms the result we saw in Figure 3.

Table 5: Price Convergence in Pre and Early Post E-Commerce Period

	(1)	(2)	(3)	(4)
Dependent Variable	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}
Lagged Price	-0.293	-0.323	-0.309	-0.126
	(0.032)	(0.037)	(0.031)	(0.013)
E-Commerce Intensity	-0.171		-0.045	0.332
× Lagged Price	(0.405)		(0.406)	(0.171)
E-Commerce Intensity		-1.158	-1.275	-0.516
× Lagged Price $\times D_t$		(0.588)	(0.315)	(0.110)
t	{1996}	{2001}	{1996,2001}	Annual 1991-2001
Observations	26,221	27,633	51,782	272,469
R^2	0.11	0.18	0.15	0.06
First-stage F	29.89	33.96	17.57	17.66
Estimation	IV	IV	IV	IV

Note: E-Commerce intensity (x^E_{i09}) is defined in equation (10); D_t is dummy variable that is one after 1996 (i.e., the post e-commerce period). Table shows regression results of equation (1) using IV: e-commerce sales intensity in 2009 is instrumented using 1999 catalog sales intensity. The first column uses the five-year log differences in prices between 1991 and 1996 and the second column uses five-year differences from 1996 and 2001. The third column uses two five-year periods, 1991–1996 and 1996–2001. The fourth column use the annual log differences in prices from 1991 to 2001. Standard errors in parentheses.

In column 3 of Table 5, we estimate our baseline differences-in-differences specification of equation (1) using a five-year differences by letting t take on two values: 1996 and 2001. The most important result for our purposes is the estimate of the coefficient on the interaction term on the e-commerce intensity coefficient. As one can see from the table, the coefficient is negative and precisely measured. Not surprisingly, the estimated coefficient on $p_{ic,t-k}$, $\hat{\gamma}$, does not change much, and we continue to get a negative and significant coefficient on the e-commerce intensity interaction term ($\hat{\delta}_2 = -1.303$). The estimate of δ_1 is close to zero, which means that before the entry of e-commerce firms, there was no difference in the rates of price convergence between goods that would ultimately be sold intensely online relative to those would not. This result is very much in line with the bottom two left-hand side plots in Figure 3.

We now turn to exploring the robustness of these results to alternative specifications. As in Table 3, we find that the OLS results (reported in the online appendix section A.3) are typically attenuated by about 20 percent, which is consistent with our instrument eliminating biases associated with measurement error. The estimates in Table 5 are likely to understate the impact of e-commerce because e-commerce firms were relatively small before 2001. In order to deal with this concern, Table 6 presents results in which we use alternative time periods. In the first three columns, we do a differences in differences based comparing the five years prior to the entry of e-commerce firms (1991-1996) with three alternative non-overlapping periods: 2001-2006, 2006-2011, and 2011-2016. In the fourth column, we use all three post e-commerce five-year periods. Although there is a significant impact of e-commerce on rates of convergence in all specifications, the results become stronger after e-commerce merchants had a chance to expand operations. For example, the coefficient on the e-commerce triple interaction ($\hat{\delta}_2$) is only -1.275 when we compare 1996-2001 with 1991-1996 (Table 5 column 4), but as one can see in first three columns of Table 6, it rises to -1.846 when we compare 2001-2006 with 1991-1996, and is even higher in later periods.

Table 6: Price Convergence Over Alternative Periods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}
Lagged Price	-0.378	-0.451	-0.373	-0.373	-0.145	-0.143	-0.145
	(0.028)	(0.032)	(0.029)	(0.026)	(0.012)	(0.015)	(0.015)
E-Commerce Intensity	0.675	1.327	0.508	0.508	0.477	0.922	0.366
$\times$ Lagged Price	(0.409)	(0.430)	(0.415)	(0.397)	(0.179)	(0.405)	(0.161)
E-Commerce Intensity	-1.797	-3.179	-1.931	-1.709	-0.791	-1.609	-0.602
$\times$ Lagged Price $\times D_t$	(0.353)	(0.318)	(0.372)	(0.245)	(0.086)	(0.214)	(0.075)
t	{1996,2006}	{1996,2011}	{1996,2016}	{1996,2001, 2006,2016}	Annual 1991-2016	Annual 1991-2016	Annual 1991-2016
Observations	52,574	43,964	43,268	88,974	581,708	579,062	578,609
R^2	0.17	0.25	0.20	0.20	0.08	0.08	0.08
E-Commerce Intensity Year	2009	2009	2009	2009	2009	2004	2014
First-stage F	15.08	23.30	19.24	17.91	17.73	21.77	8.56
Estimation	IV	IV	IV	IV	IV	IV	IV

Note: E-Commerce and catalog intensity are defined in equation (10); D_t is dummy variable that is one after 1996 (i.e., the post e-commerce period). Table shows regression results of equation (1) using 1999 catalog sales intensity as an instrument for e-commerce sales intensity. The first three columns compare the five-year period of log price differences before (1991-1996) and after the entry of e-commerce firms (2001-2006, 2006-2011, and 2011-2016). The fourth column uses data for four pooled five-year-period of log price differences from 1991 to 2016. The fifth column uses the annual frequency of log price changes and columns 6 and 7 repeat these regressions using alternative years in which to measure e-commerce intensity (x_{ib}^E). Standard errors in parentheses.

In the last three columns of Table 6, we demonstrate that we obtain similar results when we work at an annual frequency. In column 5, we continue to use x_{i09}^E as our measure of e-commerce intensity, and in the last two columns we demonstrate that our results are robust to using alternative years (2004 and 2014) in order to measure internet intensity (i.e., use x_{i04}^E or x_{i14}^E instead of x_{i09}^E). The coefficient on e-commerce intensity is significant and negative in all of these specifications.

Our results are economically significant as well. If we use the estimates in column 5 of Table 6 as a benchmark because it captures e-commerce intensity in the midpoint in our sample, we find that the half life for a relative price difference for a good not traded online is 4.4 years. By contrast, the half life for a good with maximal internet sales intensity is 1.1 years. Thus, our estimates imply that the advent of e-commerce have significantly altered the ability of retailers to charge different prices in different cities.

The second concern that one might have with the the results is that we may have a data measurement problem that is influencing the results. In order to make sure that some idiosyncratic component of the NSFIE survey method is not driving our results, we replicate all our main results using measures of e-commerce intensity based on Rakuten sales data instead. We report the results from this exercise in Appendix A.4 Table C3 for over period 1991 - 2001 and Table C4 for 1991 - 2016, which shows that we obtain very similar results regardless of whether we measure internet sales intensity using consumer expenditure data or Rakuten e-commerce sales data.

4.2.2 Gains from Arbitrage

Aggregate consumer gains due to faster price convergence can be calculated from the equation (9). One of the interesting features of these equations is that the welfare gain is proportional to the choice of demand elasticity. In all cases, we base our estimates of the impact of e-retail on the rate of convergence on Table 6 column 5. Estimating these elasticities using our

Table 7: Counterfactual Welfare Gain due to Price Arbitrage

σ	ΔW_{14}	ΔW_{17}
3	0.0020	0.0017
4	0.0026	0.0023
5	0.0033	0.0029
6	0.0039	0.0035
7	0.0046	0.0040

Note: ΔW_t equals the in welfare in each year are expressed as a share of expenditure in the previous year and is computed according to equation (9).

data is difficult because we do not have good instruments for the price of goods in each city. We therefore choose to rely on prior estimates of demand elasticities. Interestingly, estimates of elasticities for the elasticity of substitution across goods available in retail stores and across retail merchants tend to be close to four, so we will adopt that estimate as our baseline one in the welfare calculations in this section and the next. [10] Table 7 presents that welfare gain arising from price arbitrage in 2014 towards their steady state equals 0.3 percent of expenditure when the demand elasticity is 4. Low estimates of this elasticity (e.g., $\sigma = 3$) lower the estimate to 0.2 percent, whereas high estimates of the elasticity ($\sigma = 7$) yield a gain of as large as 0.5 percent, but clearly there are substantial welfare gains through this channel.

4.3 Variety Gains

An alternative mechanism through which e-commerce might affect welfare is by enabling consumers to access new varieties as in Brynjolfsson et al. (2003). One of the challenges of estimating the gains from new

[10]For example, Dolfen et al. (2019) estimate the elasticity between online and offline merchants to be 4.3. Hottman (2019) estimates the elasticity of substitution across stores with in a variety of cities and obtains a median estimate of 4.7. Hottman et al. (2016) estimate the elasticity of substitution across firms selling packaged goods for a wide range of products and obtain a median value of 3.9. Thomassen et al. (2017) estimate that the median markup for supermarkets in the UK to be 1.30, which in a CES setup with monopolistically competitive firms would correspond to an elasticity of substitution across retailers of 4.3 (where we make use of the fact that in a monopolistically competitive setting with CES preferences the markup equals $\sigma/(\sigma - 1)$.

varieties is that our data does not enable us to see which varieties became available.Fortunately, we do observe sufficient statistics that enable us to compute the welfare gain even in a world in which we do not see the underlying varieties. In order to do this, we adopt the framework of Feenstra (1994) to compute the change in the CES price index due to new varieties. He showed that the log change in the consumer price index due to new varieties can be written as:

$$\Delta \ln P_t = \frac{1}{\sigma - 1} \ln \left(\frac{\lambda_t}{\lambda_{t-k}} \right), \tag{13}$$

where $\lambda_t \in (0, 1]$ is the share of consumer of expenditures in period t on varieties available in *both* periods t and $t - k$.

In order take the theory to the data, we need to make some assumptions. First, we assume that purchasing from an e-commerce merchant differs in some way from purchasing the good from a physical store and this differentiation is captured in σ, which we continue to set equal 4 in our base case. Second, we assume that one can treat the purchase of goods in physical stores in the end period as not varying either in average quality or variety of stores over this time period. While there definitely was turnover in physical retailers over this time period, this is not a problem if the stores that exited were replaced with stores of comparable quality, so that consumers' shopping experience in physical stores remained unchanged. There is some evidence that this assumption is reasonable. For example, when Rakuten entered the Japanese market in 1997, there were 1,015 square meters of retail floor space per capita, and in 2014, this number stood at 1,061 square meters. [11] Thus, the rise of e-commerce is not associated with a fall in the amount of space used to display goods by physical merchants. Based on this, we think that it is fair to assume that consumers entering Japanese physical stores could continue to experience comparable shopping experiences.

[11] Similarly, the amount of physical retail space in Japan stayed almost constant at approximately 130 million square meters over the entire time period. Source: Japan Statistical Handbook, various years http://www.stat.go.jp/english/data/nenkan/index.html

Nevertheless, the rise of e-commerce merchants is necessarily associated with a decline in expenditure shares in other retailers. Based on the Feenstra formula, it is straightforward to see how e-commerce should affect prices. If we start in a simple case in which consumers face two choices for goods purchases—e-retail or other retail—and choose a base period ($t-k$) that predates e-commerce, it must be the case that $\lambda_{t-k} = 1$ because the initial share of purchases from e-commerce firms is zero by construction. However, the share purchased in period t (λ_t) will be less than one because consumers in the later period will only purchase a fraction of their goods from other retail stores. Thus, the price level in period t will fall because consumers now have access to new (online) varieties.

One problem with this approach is that it implicitly assumes that the elasticity of substitution between physical retailers and e-commerce merchants (σ) is the same as that between e-commerce merchants and catalog merchants. However, it may be the case that e-commerce is much more substitutable with catalog sales than it is with purchases in physical stores. If e-commerce is perfectly substitutable with catalog sales, then we should compute our λ ratios based on the purchases from physical stores divided by the sum of purchases from physical and telemarketing merchants (i.e., e-commerce and catalog merchants). In this case, the share of purchases from physical merchants in period $t-k$ (λ_{t-k}) will be less than one because consumers purchased some goods from catalogs before the entry of e-commerce firms. Similarly, we will also have $\lambda_t < 1$ because in the later period consumers purchase from both catalog and e-commerce merchants. Intuitively, the price index will fall as long as $\lambda_t/\lambda_{t-k} < 1$, which is equivalent to saying that a necessary condition for e-commerce to lower the price index is that its sales did not come completely at the expense of catalog merchants. We will refer to the price change based on this assumption as ΔP_t^T to reflect the fact that it can be thought of as the change in the price level can be thought of as the gain from telemarketing more generally.

In order to implement these calculations, we need to first adjust the data to take into account that not all consumer expenditures occur through retailers. We first do the calculation under the assumption that we can treat all retail channels other than e-commerce as continuing to sell a constant set of varieties of constant quality. Based on the NSFIE data, we know that the share of household expenditures purchased from all retailers (χ) was 0.62 in 2014, with the remaining expenditures covering utilities, education, and other expenditure items that we will assume are not affected by e-commerce's entry into the goods sectors. In 2014, e-commerce expenditures on goods as a share of all retail expenditures, which we denote by ψ, was 0.0437. The share of household expenditures from non-e-commerce firms in 2014 was therefore $\lambda = (1-\psi)\,\chi + 1 - \chi = 0.97$. Assuming an elasticity of substitution of 4, this gives us an estimate of the percentage price drop between 1996 and 2014 associated from e-commerce in Japan ($\Delta \ln P_{14}^{E}$) of 0.9 percent. We report this number in the first column of Table 8 along with a number of alternative estimates based on different plausible estimates of the trade elasticity. These consumer gains range from 0.5 percent to 1.4 percent in 2014 and from 0.6 percent to 1.8 percent in 2017. The higher numbers in later years reflect the fact that e-commerce sales continue to expand rapidly in Japan.

Table 8: Price Change Due to E-Commerce Varieties

σ	ΔlnP_{14}^{E}	ΔlnP_{17}^{E}	ΔlnP_{14}^{T}	ΔlnP_{17}^{T}
3	-0.014	-0.018	-0.015	-0.020
4	-0.009	-0.012	-0.010	-0.013
5	-0.007	-0.009	-0.008	-0.010
6	-0.005	-0.007	-0.006	-0.008
7	-0.005	-0.006	-0.005	-0.007

Note: $\Delta \ln P_{t}^{E}$ is the implied log price change associated with the entry of e-commerce firms under the assumption that elasticity of substitution between e-commerce and physical retail is the same as between e-commerce and catalog merchants. $\Delta \ln P_{t}^{T}$ is the implied log price change associated with the entry of all telemarketing firms (e-commerce and catalog merchants).

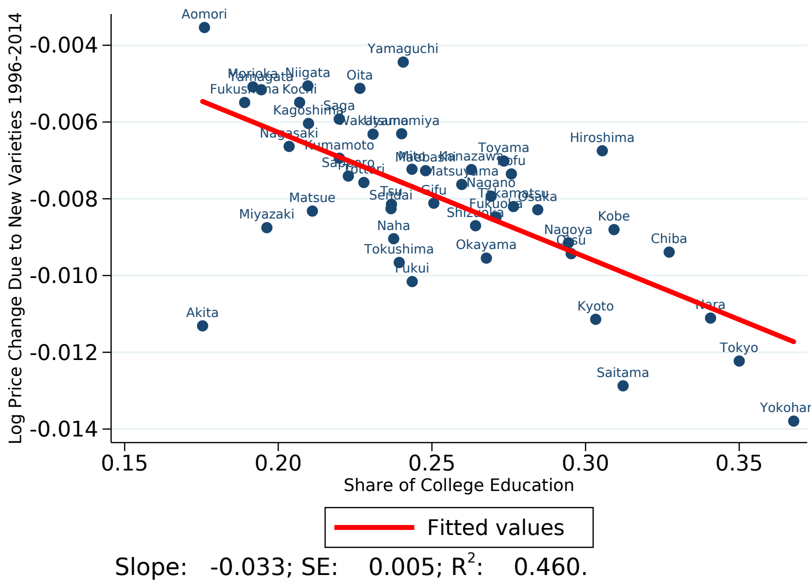
The second two columns in Table 8 define local sales as total expenditures less expenditures on products sold over the internet or through catalogs. Interestingly, we see that associated price reductions ($\Delta \ln P_t^T$) are larger when we allow for the fact that consumers purchased and continue to purchase goods through catalogs. The mechanical reason for this result is that the share of consumer expenditures through catalogs actually grew slightly between 1996 and 2014. This result may be due to the fact that all telecommunications prices fell, which benefited both catalog and e-commerce merchants at the expense of physical retailers.

The implicit gains due to varieties produces a larger estimate of the gains than the price arbitrage approach we applied in Section 4.2.2 and reflects the impact of different modeling assumptions on the welfare estimates. In the price arbitrage approach, e-commerce may generate exports of products from one city to another (which might appear in the data as e-commerce transactions) but there is no variety gain and the welfare gain arises solely from the reduction in price dispersion across cities from sales of the same product across cities. By contrast, in the variety approach consumers would gain from ability of shopping from e-commerce firms even if these merchants offered the same products at the same prices (perhaps because online shopping saves time). Since both of these approaches are plausible ways thinking about the data, we conclude that baseline estimate of the gains due to e-commerce (using an elasticity of substitution of 4) ranges from 0.3 to 0.9 percent.

One of the characteristics of calculations of the variety gains due to e-commerce is that the magnitude of these gains is driven entirely by the increase in the share of sales by e-merchants. This share is strongly correlated with the share of college graduates in a prefecture as one can see in Figure 4, which plots the implied price change due to e-commerce at the prefectural level (ΔP_{ct}^E, where c denotes prefecture) against the share of that prefecture's population with a college degree.[12] On plausible explanation for this high correlation between e-commerce use and education is that highly educated people are likely to be more comfortable using computers

[12] Japanese prefectures are roughly the size of US counties.

Figure 4: Price Change Due to New Varieties vs. Share of College Education



Note: Figure plots the log price change due to the increased variety ($\Delta \ln P^E_{14}$) from e-commerce in 2014 against the share of college education.

and other information technologies and also are more likely to use credit cards and non-cash payments. Whatever the cause, this result suggests that variety models imply a digital divide in which regions with a large share of highly educated people benefit more than regions with fewer highly educated people. [13]

One obvious concern with this plot is that the share of college educated people might be correlated with other factors that matter for internet purchases. For example, Dolfen et al. (2019) document that e-commerce in the U.S. is positively associated with city size. This is also true in Japan as well where Tokyo is both the largest city and the city with the second highest share of college-educated people. Alternatively, it may be the case that income or age may be associated with e-commerce intensity. In order to understand the robustness of our regional results to controlling for these factors, we regressed the welfare gain on population (which is a proxy for

[13]Whether we include or exclude catalog sales does not matter substantively for our prefectural results. We do not find a similar pattern when computing arbitrage gains because gains are not highly correlated with the share of e-commerce purchases in a locale.

Table 9: Correlates of Price Change Due to New Varieties

	Dependent Variable: $\Delta ln(P_{14}^{E})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of College Educated	-0.033	-0.031	-0.037	-0.030	-0.020	-0.025
	(0.005)	(0.007)	(0.006)	(0.007)	(0.008)	(0.009)
ln(Population)		-0.000				0.000
		(0.000)				(0.000)
ln(Income per Capita)			0.003			0.003
			(0.002)			(0.002)
ln(Average Age)				0.006		-0.001
				(0.009)		(0.009)
Share of Secondary Educated					0.015	0.016
					(0.007)	(0.008)
Constant	0.000	0.002	-0.019	-0.023	-0.009	-0.029
	(0.001)	(0.005)	(0.017)	(0.034)	(0.005)	(0.039)
Observations	47	47	47	47	47	47
R^2	0.460	0.461	0.474	0.465	0.506	0.526

Note: The table shows how prefectural welfare gains due to increased variety relate to characteristics of prefecture - share of the college education, population, income per capita, and share of secondary education. Standard errors in parentheses.

urban vs. rural prefectures), prefectural income per capita, and average age and report the results in Table 9. We find that none of these variables are significant once we control for the share of college educated people in a prefecture. When we include the share of secondary-school graduates, we find that it is significant in one specification, but it has a negative sign, which reinforces our earlier point that it is highly educated people that are the main users of e-commerce. In fact, most of the coefficients are precisely estimated zeros.[14] These differences are economically significant.

[14]This may explain why Fan et al. (2018) find no link between education and internet sales intensity. Chinese education levels are much lower than in Japan, which means that very few people have gone to college in their sample. The average number of years

We estimate that the e-commerce gains for a city like Tokyo with a share of college-educated people equaling 0.35 is 1.2 percent, while a city with a college share of only 0.175, like Fukushima, is only half as large.

5 Conclusion

This paper makes use of a unique Japanese data set covering hundreds of products over close to three decades to examine the impact of the e-retail on Japanese relative prices and welfare. While we find that at the national level the price increases for goods sold intensively online are lower than those sold principally in physical stores, we show that this result was present even before the advent of e-commerce. Nevertheless, the entry of e-commerce firms is associated with a widening of this gap, which is consistent with e-commerce affecting relative price increases.

At the local level, we find strong evidence that the rate at which intercity price differences converge rose significantly for goods sold intensively online after e-commerce sales became common in Japan, but goods not sold intensively online experienced no increase in the rate of price convergence. This provides evidence that information technology significantly changed pricing behavior of physical stores in Japan. Analyzing the impact of this faster rate of price convergence through the lens of the Jensen (2007) model indicates that the welfare gains due to e-commerce were sizable: Japanese welfare in 2014 was 0.3 percent higher as a result of e-commerce.

We also explore the consumer gains due to e-commerce through the lens of models featuring variety gains. These models suggest that the entry of e-commerce firms lowered variety-adjusted prices by 0.9 percent and that these gains benefitted highly educated regions more than less educated regions. Although a feature of new-trade theory models is that no location can be made worse off as a result of trade liberalization, the estimated welfare gains in relatively rich cities like Tokyo are four times higher than in small cities. This result arises from the fact that higher-educated consumers

of education in Fan et al. (2018) is only 8.8 years whereas the average in our sample of Japanese cities is 11.9 years.

buy substantially more online than less-educated consumers.

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Online Appendix to "The Impact of E-Commerce on Relative Prices and Consumer Welfare?" (Not for Publication)

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July, 2019

Table of Contents

A.1 Introduction

This online appendix contains supplementary empirical results.

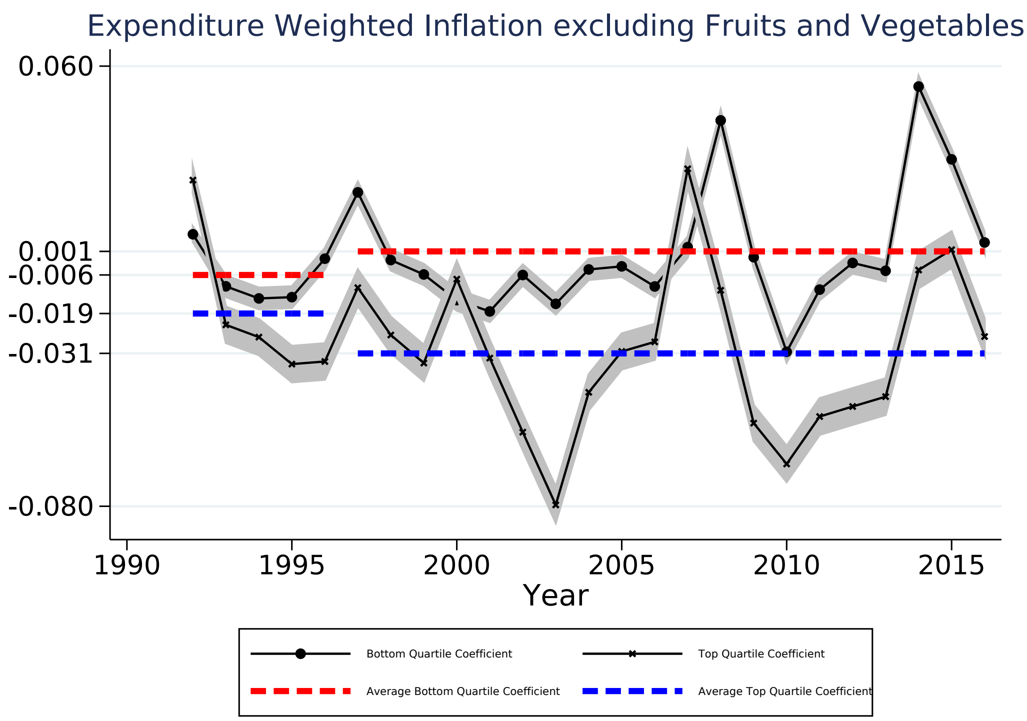
Section A.2 replicates our results on national rates of price change using alternative estimation methods. Section A.3 presents OLS versions of our specifications, and Section A.4 replicates our results using Rakuten data instead of NSFIE data to

A.2 Robustness of National Price Change Differentials

One of the most volatile sectors in the Japanese CPI are fruits and vegetables. Since these products tend to have low e-commerce intensity, we explore the sensitivity of our results to dropping these sectors. In Figure A.1, we replicate Figure 2 but drop fruits and vegetables from the sample. As one can see from Figure A.1, we still see the same pattern in the data in which goods with low e-commerce intensity have higher rates of price change than goods with high intensity. We also see this difference increase in the e-commerce period. Interestingly, in 1992, the first observation in the plot, we see that goods with high and low e-commerce intensity exhibit similar rates of price increase, but in in Figure A.1 (which includes fruits and vegetables), we see a negative rate of price increase in 1992. This demonstrates that the low rate of price change in that year is driven by the volatile fruits and vegetables sector.

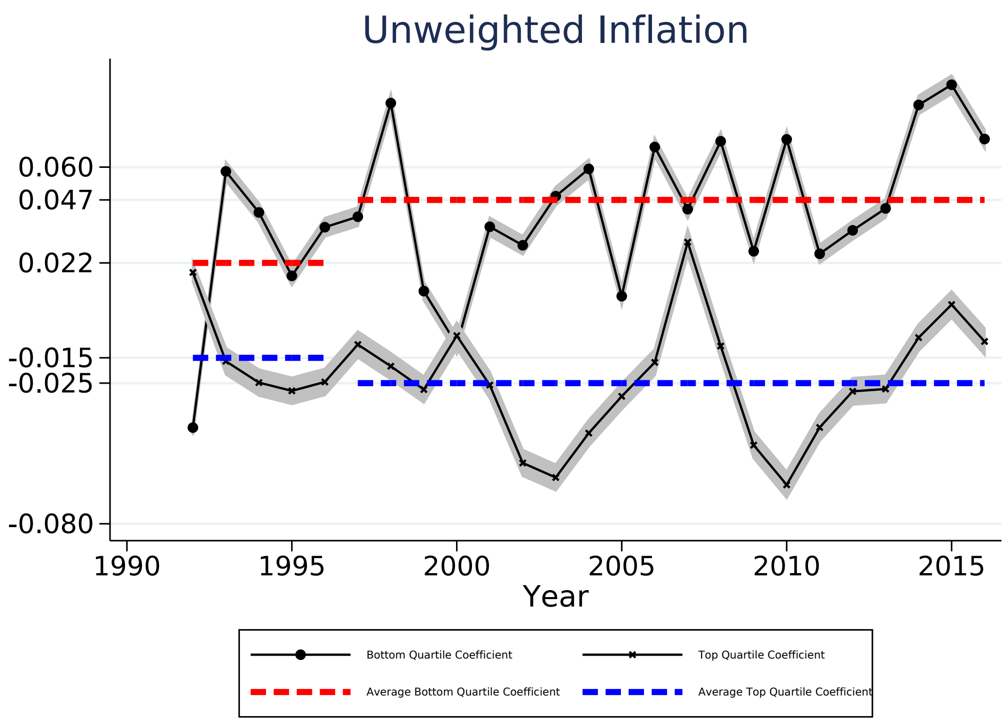
Figure 2 in the paper is based on a weighted regression of the price changes in which the weights equal the expenditures. In Figure A.2, we replicate the figure using unweighted price changes. As one can see, using an unweighted regression does not alter the qualitative result showing that goods with low e-commerce intensity have higher rates of price change than goods with high intensity and that this gap widened in the e-commerce period.

Figure A.1: Price Growth of of Goods With High and Low E-Commerce Intensity excluding Fruits and vegetables



Data source: RPS, NSFIE, and authors' calculation. Notes: This black line shows time fixed effect $\hat{\theta}_t$ from equation (12), which tells the average rate of expenditure-weighted price increase for the goods excluding the sector "Fruits and vegetables" in two groups: products with bottom quartile e-commerce sales intensity (black line with dot) and products with top quartile e-commerce intensity (black line with symbol x). The red dashed line shows the average rate of price increase before and after the entry of e-commerce firms for goods with bottom quartile e-commerce sales intensity and the blue dashed line shows that for goods with top quartile e-commerce sales intensity.

Figure A.2: Price Growth of of Goods With High and Low E-Commerce Intensity



Data source: RPS, NSFIE, and authors' calculation. Notes: This black line shows time fixed effect $\hat{\theta}_t$ from equation (12), which tells the average rate of unweighted price increase for the goods in two groups: products with bottom quartile e-commerce sales intensity (black line with dot) and products with top quartile e-commerce intensity (black line with symbol x). The red dashed line shows the average rate of price increase before and after the entry of e-commerce firms for goods with bottom quartile e-commerce sales intensity and the blue dashed line shows that for goods with top quartile e-commerce sales intensity.

A.3 OLS Regression Results

In this section, we replicate our the main results on regional price convergence in Tables 5 and B2 without instrumenting for e-commerce intensity and just using an OLS estimator. As one can see from Tables B1 and B2, the results are similar in that we observe the same basic pattern of convergence rates for e-commerce intensive goods being higher after the entry of e-commerce merchants. The coefficient on the e-commerce intensity terms is attenuated in the OLS relative the to the IV specifications. This may reflect the fact that our IV approach eliminates the attenuation bias due to classical measurement error in the e-commerce intensity variable.

Table B1: Price Convergence in Pre and Early Post E-Commerce Period (OLS regression)

	(1)	(2)	(3)	(4)
Dependent Variable	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}
Lagged Price	-0.293	-0.325	-0.312	-0.121
	(0.026)	(0.027)	(0.024)	(0.011)
E-Commerce Intensity	-0.164		-0.023	0.170
$\times$ Lagged Price	(0.268)		(0.252)	(0.112)
E-Commerce Intensity		-1.126	-1.217	-0.417
$\times$ Lagged Price $\times D_t$		(0.321)	(0.328)	(0.092)
t	{1996}	{2001}	{1996,2001}	Annual 1991-2001
Observations	26,221	27,633	51,782	272,469
R^2	0.52	0.52	0.52	0.47

Note: E-Commerce intensity (x^E_{i09}) is defined in equation (10); D_t is dummy variable that is one after 1996 (i.e., the post e-commerce period). Table shows regression results of equation (1) using OLS. The first column uses the five-year log differences in prices from 1991 - 1996 and the second column uses that from 1996 - 2001. The third column uses two five-year periods, 1991 - 1996 and 1996 - 2001. The fourth column use the annual log differences in prices from 1992 to 2001. The IV regression results are available in Table 5. Standard errors in parentheses.

Table B2: Price Convergence Over Alternative Periods (OLS regression)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}
Lagged Price	-0.392	-0.461	-0.390	-0.390	-0.150	-0.153	-0.151
	(0.019)	(0.026)	(0.019)	(0.016)	(0.009)	(0.008)	(0.009)
E-Commerce Intensity	0.646	1.090	0.485	0.487	0.357	0.365	0.249
$\times$ Lagged Price	(0.274)	(0.276)	(0.231)	(0.211)	(0.103)	(0.182)	(0.074)
E-Commerce Intensity	-1.295	-2.478	-1.387	-1.285	-0.563	-0.580	-0.381
$\times$ Lagged Price $\times D_t$	(0.250)	(0.273)	(0.324)	(0.209)	(0.079)	(0.241)	(0.057)
t	{1996,2006}	{1996,2011}	{1996,2016}	{1996,2001, 2006,2016}	Annual 1991-2016	Annual 1991-2016	Annual 1991-2016
k	5	5	5	5	1	1	1
Observations	52,574	43,964	43,268	88,974	581,708	579,062	578,609
R^2	0.53	0.58	0.63	0.60	0.42	0.42	0.43
E-Commerce Intensity Year	2009	2009	2009	2009	2009	2004	2014

Note: E-Commerce intensity (x_{ib}^E) is defined in equation (10); D_t is dummy variable that is one after 1996 (i.e., the post e-commerce period). Table shows regression results of equation (1) using OLS. The first three columns compare the five-year period of log price differences before (1991-1996) and after the entry of e-commerce firms (2001-2006, 2006-2011, and 2011-2016). The fourth column uses data for four pooled five-year-period of log price differences from 1991 to 2016. The fifth column uses the annual frequency of log price changes and columns 6 and 7 repeat these regressions using alternative years in which to measure e-commerce intensity (x_{ib}^E). The IV regression results are available Table 6. Standard errors in parentheses.

A.4 Results Using Rakuten Sales Data as a Measure of E-Commerce Intensity

In this section of the appendix, we demonstrate that all of our main results are robust to measuring e-commerce sales intensity (x_{ib}^{E}) based on Rakuten sales sales data. This establishes that our results are not dependent on any idiosyncrasies in how the Japanese government collects data on online expenditures.

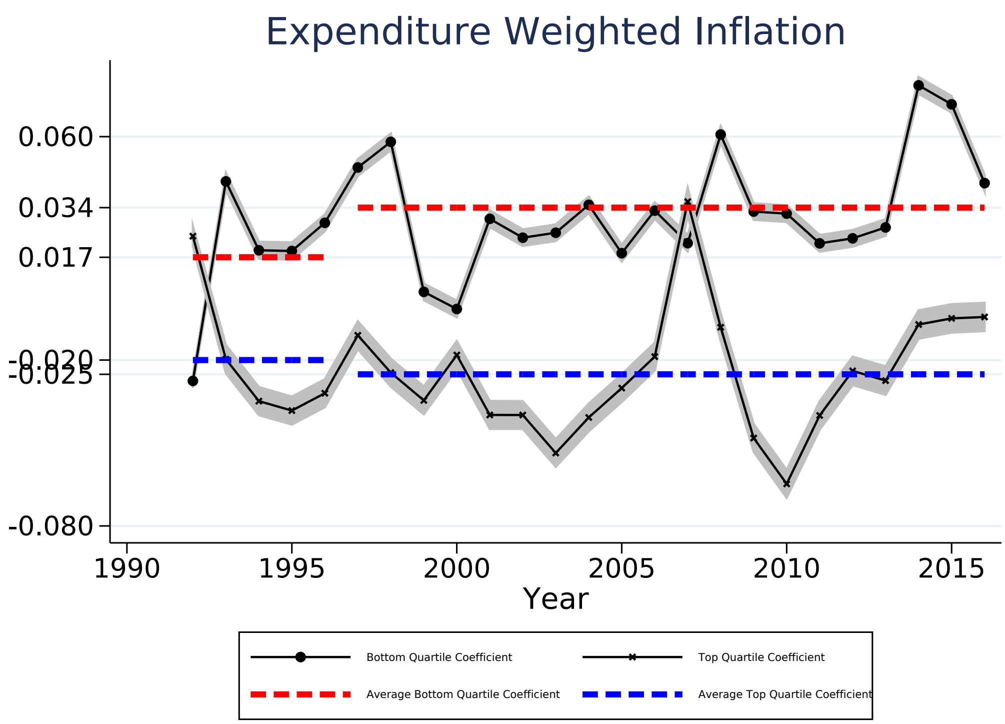
A.4.1 National Price Results

In Figure A.2, we replicate the Figure 2 using unweighted price changes. As one can see, using Rakuten data instead of NSFIE data to measure e-commerce sales intensity does not alter the qualitative result showing that goods with low e-commerce intensity have higher rates of price change than goods with high intensity and that this gap widened in the e-commerce period.

A.4.2

Tables C1 and C2 replicate Tables 3 and C2 using Rakuten data to measure e-commerce intensity. The results are qualitatively similar to those presented in the text.

Figure C1: Price Growth of of Goods With High and Low E-Commerce Intensity



Note: This black line shows the average rate of expenditure-weighted price increase for the goods in two groups: products with bottom quartile Rakuten sales intensity (black line with dots) and products with top quartile Rakuten intensity (black line with xs). The red dashed line shows the average rate of price increase before and after the entry of e-commerce firms for goods with bottom quartile e-commerce sales intensity and the blue dashed line shows that for goods with top quartile e-commerce sales intensity.

Table C1: Relative Price Changes and Rakuten Intensity

	(1)	(2)	(3)	(4)
	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}
D_t	-0.0010	0.0065	-0.0005	0.0176
	(0.0021)	(0.0021)	(0.0045)	(0.0042)
E-Commerce Intensity	-0.0079	-0.0464	-0.0149	-0.2589
$\times D_t$	(0.0144)	(0.0141)	(0.0895)	(0.0745)
Sample	Goods	Goods	Goods	Goods
Fixed Effects	Product	Product	Product	Product
Estimation Period	1992-2001	1992-2016	1992-2001	1992-2016
Observations	273,405	583,735	269,827	575,494
R^2	0.03	0.03		
First-Stage F-Stat			17.05	18.24
Estimation Method	OLS	OLS	IV	IV

Note: The dependent variable is the one-year log price change; D_t is dummy variable that is one after 1996 (i.e., the post e-commerce period); and Rakuten intensity (x^R_{i09}) is defined in equation (10). Table shows relative price changes for goods sold online intensively relative to goods not sold online intensively before and after the entry of e-commerce firms. Column 1 and 3 are for 1992-2001 and column 2 and 4 are for 1992-2016. The first two columns show OLS estimates using e-commerce sales intensity and the second two columns use catalog sales intensity as an instrument. Standard errors in parentheses.

Table C2: First Stage of Instrumental Variables Regression

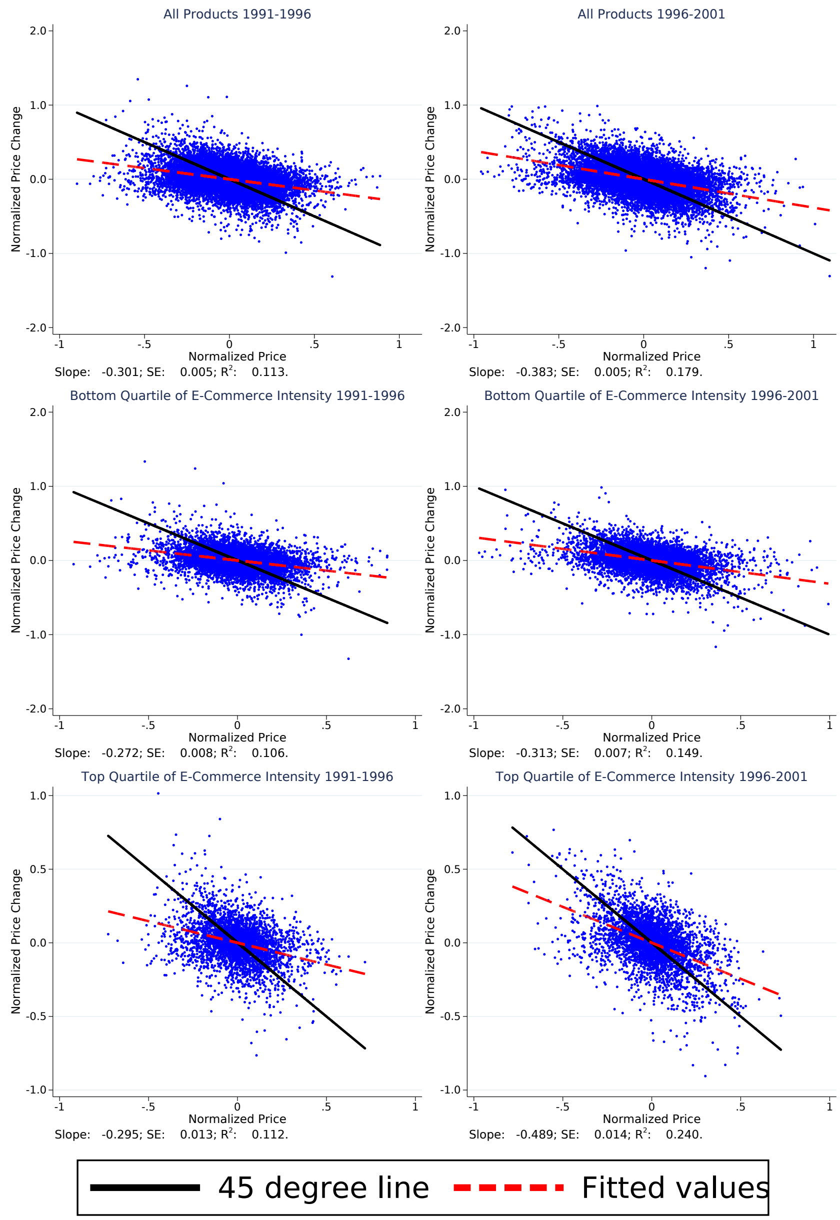
	(1) E-Commerce Intensity $\times D_t$	(2) E-Commerce Intensity $\times D_t$	(3) E-Commerce Intensity
Catalog Intensity $\times D_t$	0.4389	0.4457	
	(0.1063)	(0.1043)	
D_t	0.0277	0.0294	
	(0.0051)	(0.0052)	
Catalog Intensity			0.3561
			(0.0558)
Constant			0.0495
			(0.0041)
Sample	Goods	Goods	Goods
Fixed Effects	Product	Product	None
Estimation Period	1992-2001	1992-2016	
Observations	269,827	575,494	1,501
R^2	0.07	0.06	0.03
First-Stage F-Stat	17.05	18.24	
Estimation Method	IV-First Stage	IV-First Stage	OLS

Note: Rakuten intensity (x^R_{i09}) and catalog intensity (x^C_{i99}) are defined in equation (10); D_t is dummy variable that is one after 1996 (i.e., the post e-commerce period). The first two columns of the table present the first-stage regression results (i.e., separate observations for each city and year): column 1 shows results using data for 1992-2001, and column 2 uses data for 1992-2016. The last column presents an OLS regression using only the goods data for 2009. Standard errors in parentheses.

A.4.3 Estimation of Price Convergence Using Rakuten Data

Figure C2 replicates Figure 3 using Rakuten data to measure e-commerce intensity instead of NSFIE data. Similarly, Tables C3and C4 replicate Tables 5 and 6 using Rakuten data. The results are qualitatively the same as those presented in the text.

Figure C2: Normalized Price Change vs. Normalized Price



Note: This graph plots normalized price changes against normalized price levels. Normalized price changes (levels) equal the actual price changes (levels) less the fixed effects from a regression of price changes (levels) on product and city fixed effects. The left panel shows normalized price changes before the entry of e-commerce and the right panel shows them after the entry of e-commerce. The first panel plots for all goods, the second panel plots for goods with Rakuten intensity lower than the bottom quartile, and the third panel shows for goods with Rakuten intensity higher than the top quartile.

Table C3: Price Convergence in Pre and Early Post E-Commerce Period

	(1)	(2)	(3)	(4)
Dependent Variable	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}
Lagged Price	-0.290	-0.307	-0.299	-0.128
	(0.035)	(0.042)	(0.035)	(0.016)
E-Commerce Intensity	-0.226		-0.177	0.419
$\times$ Lagged Price	(0.514)		(0.519)	(0.259)
E-Commerce Intensity		-1.576	-1.528	-0.621
$\times$ Lagged Price $\times D_t$		(0.782)	(0.376)	(0.145)
t	{1996}	{2001}	{1996,2001}	Annual 1991-2001
Observations	26,298	27,736	51,959	273,405
R^2	0.11	0.18	0.15	0.06
First-stage F	9.90	11.62	6.10	5.78
Estimation	IV	IV	IV	IV

Note: Rakuten intensity (x^R_{i09}) is defined in equation (10); D_t is dummy variable that is one after 1996 (i.e., the post e-commerce period). Table shows regression results of equation (1) using IV: Rakuten intensity in 2009 is instrumented using 1999 catalog sales intensity. The first column uses the five-year log differences in prices from 1991 - 1996 and the second column uses that from 1996 - 2001. The third column uses two five-year periods, 1991 - 1996 and 1996 - 2001. The fourth column use the annual log differences in prices from 1992 to 2001. The OLS regression results are available in Appendix A.3 from Table B1. Standard errors in parentheses.

Table C4: Price Convergence Over Alternative Periods

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}	Δp_{ict}
Lagged Price	-0.372	-0.439	-0.367	-0.359	-0.143
	(0.034)	(0.036)	(0.032)	(0.031)	(0.015)
E-Commerce Intensity	0.700	1.423	0.531	0.435	0.553
$\times$ Lagged Price	(0.563)	(0.585)	(0.538)	(0.535)	(0.273)
E-Commerce Intensity	-2.230	-3.779	-2.205	-2.055	-0.959
$\times$ Lagged Price $\times D_t$	(0.525)	(0.485)	(0.430)	(0.320)	(0.133)
t	{1996,2006}	{1996,2011}	{1996,2016}	{1996,2001, 2006,2016}	Annual 1991-2016
Observations	52,750	44,100	43,400	89,285	583,735
R^2	0.17	0.23	0.20	0.19	0.08
E-Commerce Intensity Year	2010	2010	2010	2010	2010
First-stage F	5.29	7.60	7.07	6.30	6.31
Estimation	IV	IV	IV	IV	IV

Note: Rakuten and catalog intensity are defined in equation (10); D_t is dummy variable that is one after 1996 (i.e., the post e-commerce period). Table shows regression results of equation (1) using 1999 catalog sales intensity as an instrument for e-commerce sales intensity. The first three columns compare the five-year period of log price differences before (1991-1996) and after the entry of e-commerce firms (2001-2006, 2006-2011, and 2011-2016). The fourth column uses data for four pooled five-year-period of log price differences from 1991 to 2016. The fifth column uses the annual frequency of log price changes. Standard errors in parentheses.