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Item Type	Article;Peer-Reviewed;Published version
Authors	Genc, Ismail
Citation	Genc, I. H. (2021). The impact of technology on regional price dispersion in the US. Technological and Economic Development of Economy, 27(6), 1281-1300. https://doi.org/10.3846/tede.2021.15238
DOI	10.3846/tede.2021.15238
Publisher	VGTU
Download date	2025-01-24 20:30:51
Link to Item	http://hdl.handle.net/11073/23890

Technological and Economic Development of Economy
ISSN: 2029-4913 / eISSN: 2029-4921
2021 Volume 27 Issue 6: 1281–1300
https://doi.org/10.3846/tede.2021.15238

THE IMPACT OF TECHNOLOGY ON REGIONAL PRICE DISPERSION IN THE US

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Received 23 March 2020; accepted 11 April 2021; first published online 12 October 2021

Abstract. We analyze the behavior of inflation in the era of fast pace information thanks to technological advances, especially internet. Owing to readily available information, prices/inflation should quickly converge under perfect competition. To this end, we explore the possibility of price convergence in regional inflation in the USA including the permanency of such a phenomenon if observed, a concern for monetary policy makers. Empirically, we analyze standard deviation of regional inflation with special attention to technology. We show that standard deviation of inflation is not constant over time, but not necessarily ever-declining. Technology seems to help reduce price dispersion across regions.

Keywords: inflation differentials, inflation persistence, convergence, technology, structural break.

JEL Classification: E31, E52, L86.

Introduction

Convergence in prices (or inflation) across different regions of the same country is a conceptually plausible idea, especially if markets are perfectly competitive, barring any other impediments against perfect competition. Under these circumstances, there must be a downward pressure on prices so that economic profits decline to zero. One of the conditions of achieving perfect competition is to make information costless for all market participants. Recent developments in information technology have the potential to make price information widely available. This is because as technology helps disseminate price information, especially within the boundaries of the same country, the whole country would be potentially turning into a single market with little to no barriers to entry for companies, and little cost of price search for customers. Eventually prices would converge in the entire country.

Furthermore, economists have long argued that advances in technology would increase productivity (Goodfriend, 2002) by lowering the need for more labor, energy and other ma-

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terials, another step toward perfect competition. Better technology may also connote production process improvements and efficiency, again likely leading to lower prices by encouraging competition. Mincer and Danninger (2000) argue that even with full employment, technology would contribute to the growth of capacity, thus inhibiting wage induced inflation. Assuming that it happens on a broader scale in the country, we expect convergence to the same (and arguably lower) level of inflation.

While the impact of technology on productivity has been discussed widely in the literature, the role of the internet has received little attention. (For the debate in the literature about the status of "productivity," and its impact on the economy or even its measurability, see, inter alia, Gordon (2014) and Brynjolfsson and McAfee (2012) about opposing views on the issue). Evidently, the internet has allowed many companies to gain access to many markets, which had been beyond their reach due to physical boundaries. For example, Amazon, an internet based company, has captured about half of the e-commerce in the United States as well as five percent of retail sales by the end of 2018 (eMarketer Editors, 2018) with profound impact on prices in the country. In this process, Amazon has come to embody a grand vehicle of price information transmission. If Amazon in the last 10 years put downward pressure on prices, much the same way as Walmart did in 1980s–1990s, then we would expect all prices to converge to some common value (the so-called Amazon effect). That is a decline in the variation in prices. Normally such a decline in prices is associated with lower prices everywhere as competitors will try to keep up with competing prices offered by Amazon, which are presumably lower. Amazon affects both consumer behavior and traditional business models alongside e-commerce. Briefly speaking the so-called Walmart effect refers to the impact of Walmart on local businesses and consumers. While Walmart is considered to drive local stores out of business, it is also found to reduce inflation by forcing prices down in places it operates. Given the large presence of Walmart across the US, it is deemed to have a significant effect on inflation (among its other economic effects) (Fishman, 2007). According to Microdinc (n.d.), a web-technology provider, "92 percent of shoppers prefer stores with mobile platforms." Lampertius (2019) provides a discussion on similar lines. Eventually, this effect results in the disappearance (or decline) of price dispersions across places/time. Price dispersion is the variation in the price of a particular commodity (good or service) at different locations (firms). Price dispersion may arise because of search costs (see, inter alia, Zhao, 2006), information costs (see, inter alia, Dubois & Perrone, 2018), mark-ups, geographical trading frictions (see, inter alia, Gopinath et al., 2011; Choi et al., 2019), and firms' intentional efforts to attract consumers with certain preferences (see, inter alia, Varian, 1980) as well as many other features of non-perfectly competitive markets. In a general sense, this is the violation of the law of one price, or purchasing power parity if all goods and services are included.

In studies similar to ours (see, inter alia, Berardi et al., 2017), price dispersion is measured by the standard deviation (or variation) of prices, and the coefficient of variation of prices. The range of prices, which is the difference between the highest and lowest prices, lends itself more readily to item level price data. Standard deviation shows the amount of variation (dispersion) in data, which is, in our case, regional prices (inflation). We use inflation rather than prices, as shown below, due to the time series properties of these variables. The advantage of standard deviation and similar measurements, such as the coefficient of variation from the same population, lies in the fact that they do not suffer from the unit of measurement differences (Castro, 2004). In other words, they largely yield the same results when compared to each other. For example, the coefficient of variation, which expresses the standard deviation as a percentage of the sample or population mean, is simply adjusted for the mean of data, but otherwise, remains as another expression of the standard deviation. A small standard deviation points to a small spread (dispersion) around the mean. An ever-declining standard deviation indicates convergence. Pan et al. (2004) and Baye et al. (2006) provide a long list of articles which use these methods to measure price dispersion across a variety of markets in a number of countries. On a related note, in the economic growth literature, sigma-convergence employs standard deviation as a workhorse to test the validity (efficacy) of the convergence theory. There, a decline in the standard deviation of regional income and/or prices would point to convergence (law of one price), which is the timewise elimination of significant differences (dispersion) in income and/or prices on integrated markets.

In this study, we measure price dispersion as the standard deviation of regional inflation in the US after accounting for the impact of technology, in particular, the internet. The internet is the platform on which e-commerce thrives. Conceptually speaking, consumers should have all the information they need to search for "best" prices, and firms should "adjust" the prices if necessary across stores online with little cost. Practically speaking, one might rightfully argue that e-commerce is still a modest fraction of the US retail market. That would naturally have an insignificant impact on price indices such as CPI. However, we note that the Office for National Statistics' (ONS) will consider e-commerce to calculate inflation (Isaac, 2018). Even then, the widely available prices online together with fast delivery services would force brick and mortar stores to follow the suit, thus reducing price dispersion across large swaths of territory with otherwise physically segregated markets. We would expect that decline in price dispersion to continue as the share of e-commerce increases in the future (Ciccarelli & Osbat, 2017; Charbonneau et al., 2017; Hatzius et al., 2017).

On the other hand, even if we find the so-called Amazon effect on prices, the question is about its permanency; that is, will this impact disappear over time, as the Amazon effect dies out just the same way as the aforementioned Walmart effect has stabilized? Putting it differently, should there be a concern for the monetary policy maker with respect to the Amazon effect? Both the practitioners and academics already warn that policy makers should not ignore the role of technology companies such as Amazon, Google, and Uber in forcing prices down (El-Arian, 2019). Likewise, the Amazon effect has its impact on the fiscal and legal policies (Russell et al., 2018). If we find that there is no particular impact on prices across time, then we can conclude that even if there is an Amazon effect, it is just temporary, and will disappear much the same way as the so-called Walmart effect did. On the other hand, a permanent impact would potentially lead to differentials in real interest rates in different parts of the country. That may have welfare effects over time across regions (Ogawa & Kumamoto, 2008).

Basically, the Amazon effect is the "information pervasiveness" of prices in the market thanks to technology. In other words, it seeks to answer the question about whether the price information can be quickly broadcast across consumers (buyers) and producers (sellers) to allow them to react to it. In the case of the so-called Amazon effect, this would be a reduction in prices. In a perfectly competitive market, theoretically speaking, everybody knows everything all the time, thus, prices are adjusted so quickly that no one can impose monopolistic profit generating prices in the market. This leads to a reduction in price dispersion. Sellers may have to keep adjusting prices as many times as needed by the competitors' prices. Yet, producers may not be at so much liberty to frequently change prices because they do not want to be violating a "covenant" with consumers about offering their products at perfectly competitive prices (Blinder, 1994). This very fact may counterintuitively prevent producers from adjusting their prices, say downward, even if the market may suggest it. This may prevent a reduction in price dispersion.

In this study, we investigate if, in fact, there is a price converge across a number of US regions over time in the form of a reduction in the standard deviation of regional inflation. Moreover, if we find such a decline, we would like to check whether it is permanent or transitory, i.e., if it exists in some period but disappears in another. We also try to explain the behavior of price dispersion by some explanatory variables, in particular technology. In conducting our analysis, we carry out some robustness checks to make sure that the usage of the standard deviation, as opposed to some other measures of dispersion, does not artificially produce the results obtained in this study. Likewise, we wish to make sure the use of regional inflation rather than the US inflation does not artificially lead to the results we obtain. Additionally, as we perform both univariate and multivariate analyses, we compare findings to assess robustness from another perspective.

The paper is structured as follows: In the next section, we discuss the relevant literature. This is followed by the data and the variables. The econometric analyses including the pre- and post-estimation tests are presented in the Analysis section. Then, the findings are discussed in conjunction with the literature. The last section concludes the paper.

1. Literature review

There is a large and still growing literature on the impact of technology and related issues on prices/inflation across geographical locations over time. However, it is hard to state that there is a consensus on the likely impact.

Justification for convergence:

Federal Reserve Bank of St. Louis (2018) observes that inflation has recently been in decline due to a number of reasons such as the eliminated need for certain products thanks to modern alternatives serving more uses. For example, smart phones have rather eradicated the need for cameras leading to ever decreasing prices of the latter. On the other hand, new modes of economic activity such as the "sharing economy" have brought previously underused resources into the economy, thus leading to higher productivity. Recently emerging demographic dynamics has also led to similar outcomes where older people with more reliable work ethics take jobs for lower wages (lower costs to companies). All of these point to lower prices, and eventually lower inflation, and more so online than offline (Goolsbee & Klenow, 2018).

Arguably, online price convergence is more likely than offline as online markets have a special feature their offline counterparts largely lack (Gorodnichenko et al., 2018a; Cavallo, 2018). For example, online buyers have low search costs across a large number of sellers in a relatively short period of time to compare prices. In some cases, one may consider computer aided search tools, further reducing the cost of price comparisons. The same is true for online sellers that would monitor competitors' prices, and adjust to them. It is also relatively cheap for sellers to adjust prices due to low menu costs online. Obviously, if one consumer and/or seller does that, all others would follow the suit, leading to similar (if not identical) prices. However, Cavallo (2017) finds that, at least in the United States, differences in online prices from the offline ones are not necessarily led by Amazon prices.

Additionally, Yi and Choi (2005) hypothesize that the Internet improves productivity and thus reduces inflation. They find that if the number of internet users in the population increases, inflation tends to drop somewhat.

Justification for lack of convergence:
Some of the above-mentioned features of online companies' ability to frequently synchronize prices have been disputed. As indicated above, this may be because such a behavior might be considered breaking an implicit contract with customers (Blinder, 1994; Rotemberg, 2011). Hence, Ellison and Ellison (2009) and Gorodnichenko et al. (2018b) fail to find the counterpart of the so-called law of one price online. An impediment to prevent an overall price convergence including online and offline prices is the existence of non-tradables, in this case the so-called online non-tradable commodities. At least given the current technology, we will continue to have barbers around the corner in the city even if some close or distant substitutes may emerge online.

2. Data

We collect monthly data from the FRED database of St. Louis Federal Reserve on a number of variables. The first variable is the monthly regional prices in the form of "Consumer Price Index for All Urban Consumers: All items" in New York-Newark-Jersey City, NY-NJ-PA, Philadelphia-Camden-Wilmington, PA-NJ-DE-MD, Boston-Cambridge-Newton, MA-NH, Chicago-Naperville-Elgin, IL-IN-WI, Detroit-Warren-Dearborn, MI, Houston-The Woodlands-Sugar Land, TX, and San Francisco-Oakland-Hayward, CA, with an index value of 100 in the 1982–1984. The data are not seasonally adjusted. Data period is 1950m1–2018m12.

We also gather data on several technology indicators with varying data coverage periods. We choose the San Francisco Tech Pulse, Index Jan 2000 = 100, Monthly, Seasonally Adjusted, which has the largest data span among the options we review. It runs from 1971m4 to 2018m10 on a monthly basis. The index is defined by the data source as "(t)he Tech Pulse Index is a coincidence index of activity in the U.S. information technology sector. The index is interpreted as the health of the tech sector. The indicators used to compute the index include investment in IT goods, consumption of personal computers and software, employment in the IT sector, industrial production of the technology sector, and shipments by the technology sector" (Federal Reserve Bank of San Francisco, 2019). This technology indicator is denoted by TECH6.

For the sake of robustness, we also experiment with other definitions of technology. Other technology indicators are:

- San Francisco Tech Pulse, Percent Change from Year Ago, Monthly, Seasonally Adjusted;
- San Francisco Tech Pulse, Percent Change, Monthly, Seasonally Adjusted;
- San Francisco Tech Pulse, Percent Change at Annual Rate, Monthly, Seasonally Adjusted;
- Consumer Price Index for All Urban Consumers: Information technology, hardware and services, Index Dec 1988 = 100, Monthly, Not Seasonally Adjusted;
- Consumer Price Index for All Urban Consumers: Information technology, hardware and services, Index Dec 1988 = 100, Monthly, Seasonally Adjusted;

Additionally, we employ the M2 Money Stock, Billions of Dollars, Monthly, Seasonally Adjusted (M2SL). Its coverage period is 1959m1–2018m12.

We also have some variables in the quarterly frequency. One of them is the Real Gross Domestic Product, Billions of Chained 2012 Dollars, Quarterly, Seasonally Adjusted Annual Rate (GDPC1) as an indicator of the overall economic activity for the period of 1950q1–2018q4. Similarly, we collect quarterly data on the US CPI (CPIAUCSL), which are seasonally adjusted, with the coverage period of 1950q1–2018q4.

We then convert monthly data to quarterly frequency, from which we compute regional inflation for every period as the first difference of the natural logarithm of price data. Finally, we calculate average regional inflation per quarter, and the standard deviation of regional inflation (STDEV) per quarter. We employ the standard deviation as the indicator of regional inflation dispersion because it measures the variation of regional inflation data with respect to the average inflation in those regions for the period under consideration. Furthermore, we seasonally adjust the data as necessary.

In further preparation for the analysis below, we generate growth rates of the technology indicator and that of the monetary aggregate (M2SL). Both of them are computed as the first difference of the logged variable. Hence, DLTECH6 and DLM2SL represent technology and the money, respectively. We also use the income gap, denoted by HPC, which is calculated as the cycle from the HP filter of Real Gross Domestic Product à la Hodrick and Prescott (1997).

3. Analysis

To eliminate the possibility of data specific results in the rest of the paper, we first compare the overall US inflation to the average regional inflation. Figure 1 shows the US inflation vs. the average regional inflation. Likewise, Table 1 provides descriptive statistics for the two series. We also conduct an ADF test on the ratio of the average regional inflation to the US inflation, which yields a test statistic of –15.85. In addition, a two-sided mean equality test of this ratio produces a marginal significance level of 0.45, strongly failing to reject the null hypothesis of mean equaling one. Hence, we observe a close relationship between the two series. This inference indicates that the regional inflation data are not an aberration, but more like a representation of its US counterpart.

Moving forward with the regional inflation, we measure the price dispersion via standard deviation of the regional inflation per quarter as shown in Figure 2. We observe that high

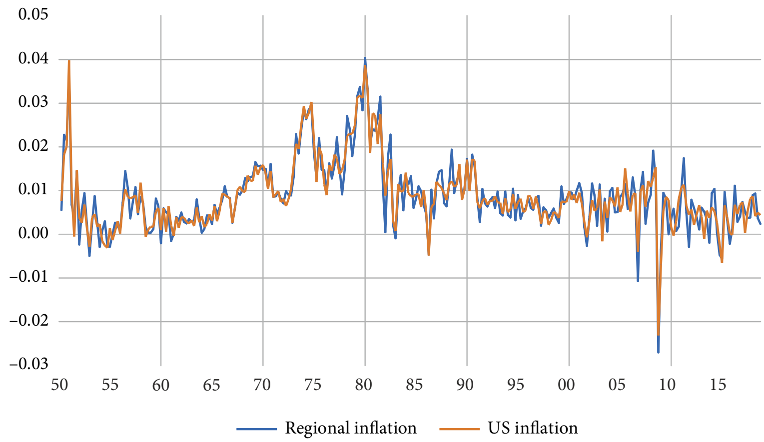

Figure 1. US vs average regional inflation

Table 1. Descriptive statistics of US and regional inflation

	US inflation	Average regional inflation
Mean	0.008625	0.008689
Maximum	0.039828	0.040349
Minimum	–0.023168	–0.027073
Std. Dev.	0.007685	0.008079

Note: Sample: 1950q2–2018q4.

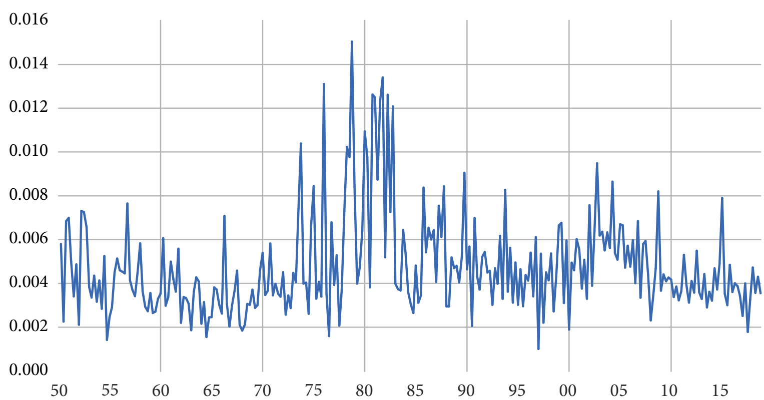

Figure 2. Standard deviation of regional inflation

inflation dispersions of the mid-1970s disappeared toward mid-1980s, which may reveal the Walmart effect. As a robustness check, we also generate the coefficient of variation for our data. A simple Satterthwaite (1946), Welch (1951) type t test, which allows the possibility of unequal variances, produces a statistics of –0.060764 with a corresponding p-value of 0.9516, meaning that we fail to reject the null hypothesis of equal means. Therefore, without loss of generality, we concentrate on the standard deviation as the measure of price dispersion in this study for both univariate and multivariate models.

Models to run:

Initially, we analyze the time series properties of univariate data. We follow this with a multivariate analysis to explain determinants of standard deviation of regional inflation in the US.

As shown in Tables 2 through 4 via CMR (Clemente et al., 1998), ZA (Zivot & Andrews, 1992) and ADF (Dickey & Fuller, 1979) tests, we find that STDEV, DLTECH6, HPC, and DLM2SL variables are stationary. Therefore, we are allowed to employ the so-called Bai-Perron method due to Bai and Perron (1998, 2003a, and 2003b) to analyze our data.

Table 2. CMR tests

Variable	Period	Additive Outlier (AO)			Innovational Outlier (IO)		
		AR Model	Min *t*	Optimal Breakpoints	AR Model	Min *t*	Optimal Breakpoints
STDEV	1950q1–2018q4	4	–5.002	1978q2, 1982q2	0	–15.991	1977q3, 1982q3
DLTECH6	1971q2–2018q4	1	–7.682	1983q4, 2000q4	1	–7.858	2000q3, 2002q3
HPC	1950q1–2018q4	1	–6.357	2006q2, 2007q4	2	–7.662	2005q1, 2008q1
DLM2SL	1959q1–2018q4	0	–8.662	1987q4, 1995q4	4	–6.006	1969q4, 1982q4

Note: Min *t* is the minimum *t*-statistics calculated. The 5% CV is –5.490. Maxlag is 4. The 5% of data are trimmed on both ends. H0: the series has a unit root with structural break(s) vs H1: the series is stationary with break(s).

Table 3. ZA tests

Variable	Period	Break in	Opt lags	Min *t*	Breakpoints	5% CV
STDEV	1950q1–2018q4	T	3	–5.344	1981q1	–4.42
		C, T	3	–6.109	1978q1	–5.08
DLTECH6	1971q2–2018q4	T	1	–6.644	2008q4	–4.42
		C, T	1	–7.23	2000q3	–5.08
HPC	1950q1–2018q4	T	2	–6.421	2012q4	–4.42
		C, T	2	–7.091	2008q4	–5.08
DLM2SL	1959q1–2018q4	T	0	–7.574	1962q2	–4.42
		C, T	0	–8.511	1987q1	–5.08

Note: Opt lags are chosen via BIC. T stands for trend, whereas C stands for the intercept.

Table 4. ADF tests

Variable	Period	Break in	Opt lags	Min *t*	5% CV
STDEV	1950q1–2018q4	C		–11.377	–2.879
		C, T		–11.384	–3.429
DLTECH6	1971q2–2018q4	C		–4.373	–2.884
		C, T		–4.922	–3.438
HPC	1950q1–2018q4	C		–4.275	–2.879
		C, T		–4.268	–3.429
DLM2SL	1959q1–2018q4	C		–7.025	–2.881
		C, T		–7.346	–3.432

Note: Opt lags are chosen via BIC. T stands for trend, whereas C stands for the intercept.

Univariate analysis of STDEV:

The univariate analysis of STDEV via the Bai-Perron method is shown in Table 5. Figure 3 shows the estimated break periods as well as the residual from the univariate analysis of STDEV. The estimated dependent variable seems to track the actual values of the dependent variable. The residuals also appear to be largely within the two-standard deviation upper and lower bounds. Additionally, the Breusch-Godfrey Serial Correlation LM Test whose null hypothesis is that there is no serial correlation at up to 12 lags yields a p-value of 0.0934 for the *Observations*$*R^2$ statistics pointing to failing to reject the null hypothesis. Combined with the graph of residuals we infer that the estimation is reasonable.

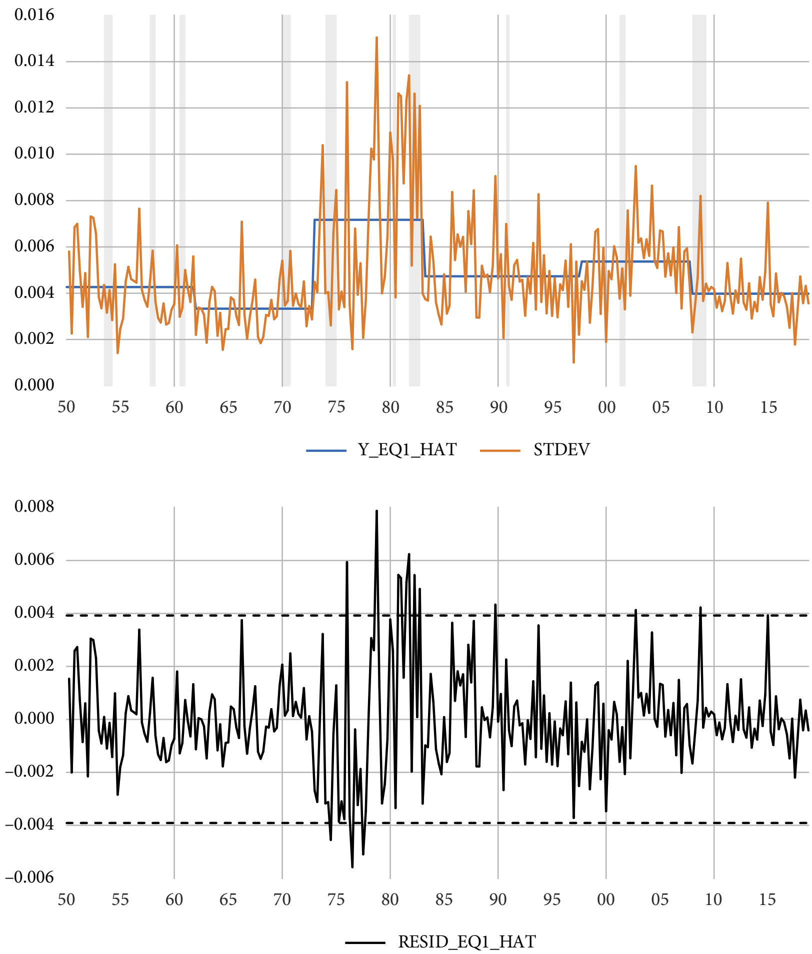

Figure 3. Univariate estimate of STDEV via BP method. Y_EQ1_HAT stands for the estimated values of STDEV whereas RESID_EQ1_HAT shows the residuals from the equation. Shaded areas in the top panel are the recession dates. These are NBER based recession indicators for the United States from the period following the peak through the trough, +1 or 0, quarterly, not seasonally adjusted (USRECQ) (source: Federal Reserve Bank of St. Louis, 2019)

Table 5. Univariate estimation of STDEV via Bai-Perron

Sub-periods	Coefficient	*t*-statistic
1950Q2–1961Q4 -- 47 obs	0.00427	14.94
1962Q1–1972Q4 -- 44 obs	0.00333	11.30
1973Q1–1983Q1 -- 41 obs	0.00717	23.46
1983Q2–1997Q3 -- 58 obs	0.00473	18.40
1997Q4–2007Q4 -- 41 obs	0.00537	17.56
2008Q1–2018Q4 -- 44 obs	0.00398	13.49
Adj R^2	0.256365	
F-statistic (*Prob*(*F*-statistic))	19.89 (0.00)	

Note: Sample (adjusted): 1950Q2 2018Q4. Break type: Bai-Perron tests of 1 to M globally determined breaks. Selection: Highest significant, Trimming 0.15, Sig. level 0.05.

The estimated breaks in the dependent variable, i.e., STDEV, are 1962q1, 1973q1, 1983q2, 1997q4, and 2008q1. The change from high inflationary periods of mid-1970s toward mid-1980s are clearly marked in the estimation output as also attested via the break dates immediately before and after that experience, namely 1973q1 and 1983q2. We earlier referred to this phenomenon as the Walmart effect. In general, we observe that higher STDEV estimations are associated with more frequent recession experiences. This is expected as the economy swings between boom/bust episodes, prices in the economy experience fluctuations leading to higher inflation standard deviation. Finally, it is revealed that one of the lowest estimated STDEV values is in the 2008–2018 period. However, that may be due to the economic crisis experienced in that period.

Multivariate analysis of STDEV:

We now turn to a multivariate analysis of STDEV. We borrow some variables from the so-called quantity theory of money. The quantity theory of money is $MV = Py$ where M stands for a monetary aggregate, V for the velocity of money, P for the price level, and y for the real income. Based on this relationship, inflation, p, can be expressed as $p = m + v - y$ where lower case variables represent growth rates of the aforementioned variables. That means we use indicators of economic activity (income gap) and money growth rate in addition to the indicator of technology. Thus, our model is

$$STDEV = \alpha + \beta DLTECH6 + \gamma HPC + \varphi DM2SL + \epsilon,$$

where the notation follows the discussion above. In other words, the dependent variable, STDEV, is the standard deviation of regional inflation. DLTECH stands for the growth rate of the San Francisco Tech Pulse. We also use the income gap, HPC, as well as the growth rate of the broad monetary aggregate, DLM2SL. With the help of this equation, we hope to measure the relative impact of technology on the dispersion of regional inflation versus other economic variables such as GDP and M2. We continue using the Bai-Perron framework as mentioned above. The results are in Table 6.

Figure 4 shows the estimated break periods as well as the residual from the multivariate analysis of STDEV. The estimated dependent variable seems to track the actual values of the dependent variable. The residuals also appear to be largely within the two-standard deviation upper and lower bounds. Additionally, the Breusch-Godfrey Serial Correlation LM Test whose null hypothesis is that there is no serial correlation at up to four lags yields a p-value of 0.1644 for the *Observations**R^2 statistics pointing to failing to reject the null hypothesis. Combined with the graph of residuals we infer that the estimation is reasonable.

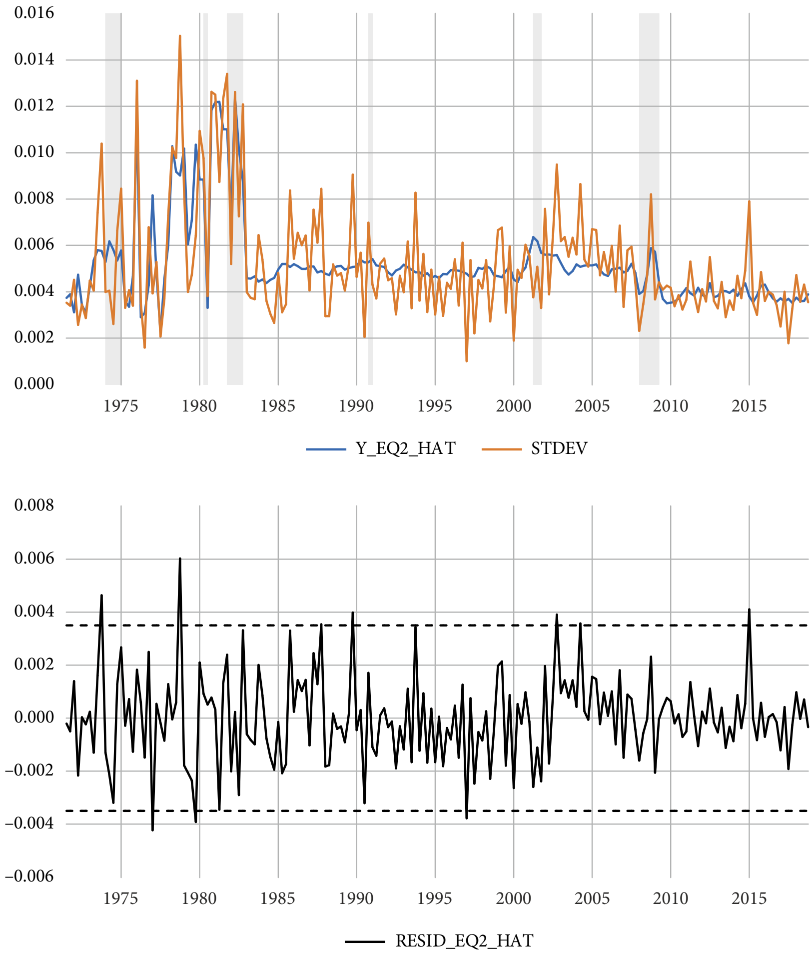

Figure 4. Multivariate estimate of STDEV via BP method. Y_EQ2_HAT stands for the estimated values of STDEV whereas RESID_EQ2_HAT shows the residuals from the equation. Shaded areas in the top panel are the recession dates. These are NBER based recession indicators for the United States from the period following the peak through the trough, +1 or 0, quarterly, not seasonally adjusted (USRECQ) (source: Federal Reserve Bank of St. Louis, 2019)

Table 6. Multivariate estimation of STDEV

Sub-period	Variables							
	Intercept		DLTECH6		HPC		DLM2SL	
	Coef	*t* stat	Coef	*t* stat	Coef	*t* stat	Coef	*t* stat
1971Q3–1975Q4 -- 18 obs	0.0082	5.0358	–0.012	–0.734	1.03E-06	0.233	–0.140	–2.445
1976Q1–1978Q1 -- 9 obs	0.0138	3.0577	–0.169	–4.382	–6.06E-05	–2.836	0.148	1.003
1978Q2–1980Q3 -- 10 obs	0.0118	2.7413	0.046	1.028	1.65E-06	0.225	–0.380	–2.925
1980Q4–1982Q4 -- 9 obs	0.0114	3.1149	–0.106	–2.277	2.63E-05	2.773	0.277	1.303
1983Q1–2007Q4 -- 100 obs	0.0052	13.7394	–0.008	–1.859	–1.91E-07	–0.144	–0.005	–0.226
2008Q1–2018Q4 -- 44 obs	0.0041	5.5569	–0.015	–1.516	–5.15E-07	–0.290	–0.008	–0.172
Adjusted *R*-squared	0.4904							
F-statistic	8.9072							
Prob(*F*-statistic)	0.0000							

Note: Sample (adjusted): 1971Q3 2018Q4. Break type: Bai-Perron tests of 1 to M globally determined breaks. Selection: Sequential evaluation, Trimming 0.05, Sig. level 0.05.

Additionally, we employ the CUSUM (Figure 5) and CUSUM of squares (Figure 6) charts to assess the parameter stability of our estimation. Since the cumulative sum of the recursive residuals falls inside the five percent critical boundaries, we infer parameter stability in the estimated equation. Likewise, since the cumulative sum of the squares falls inside the five percent critical boundaries, we further infer that the residual variance is stable.

Therefore, we conclude that the equation does not suffer from serial correlation, and its coefficients are stable over the sample. The equation is valid overall.

Going back to the estimation results in Table 6, we make the following particular observations:

- 1971q3–1975q4: Other than the intercept, money growth rate has the highest and most significant impact on the variability of inflation across regions in the US. Marginal changes in the technology indicator have a negative but insignificant impact on STDEV.
- 1976q1–1978q1: Other than the intercept, overall macroeconomic conditions, as represented by HPC, and the technology indicator affect STDEV. Nevertheless, the technology indicator has the largest impact.
- 1978q2–1980q3: Other than the intercept, the only significant variable is the money growth rate, which is negative.
- 1980q4–1982q4: Other than money, all other variables significantly affect STDEV. Technology is once again the biggest (and negative) influencer.
- 1983q1–2007q4: Other than the intercept, the only statistically significant variable at 6.5% is technology.
- 2008Q1–2018Q4: Other than the intercept, no variable has a statistically significant impact on the standard deviation of regional inflation in this sub-sample period.

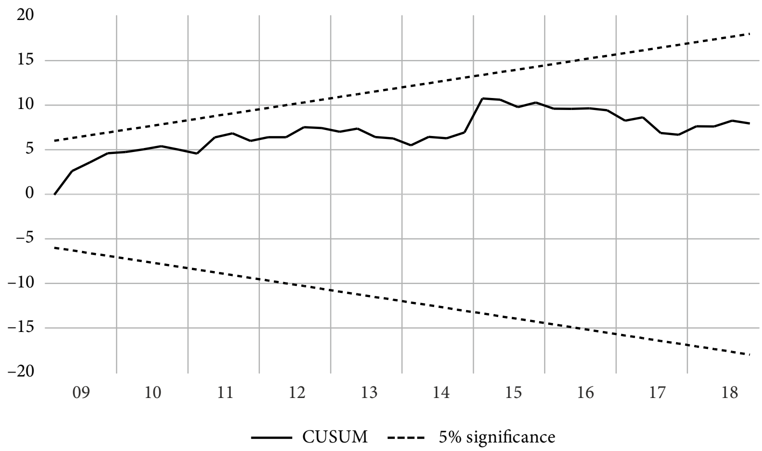

Figure 5. CUSUM of the multivariate estimation

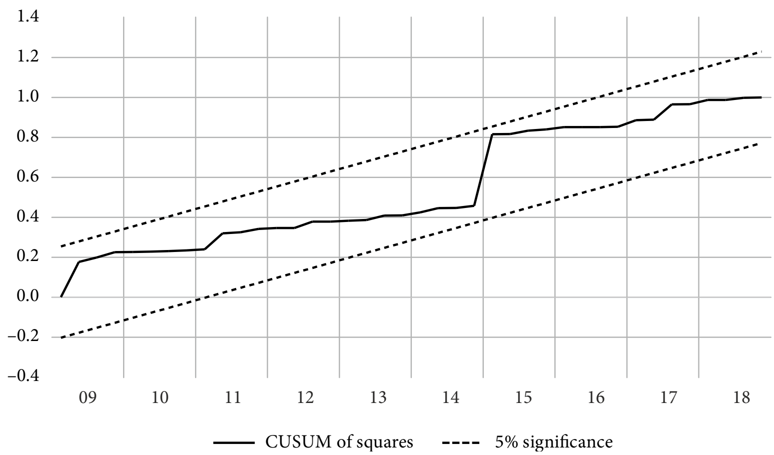

Figure 6. CUSUM of squares of the multivariate estimation

Observations on the intercept of both models:

It is worth noting that considering only the estimates of the intercept obtained from the univariate estimation as shown in Table 5 and the multivariate estimation as shown in Table 6, the simple average of the value of the sub-periods of 1971q3–1975q4, 1976q1–1978q1, 1978q2–1980q3, and 1980q4–1982q4 is 0.011 (from the multivariate estimation). This is very close to the estimated value of 0.0072 for 1973q1–1983q1 sub-period (from the univariate estimation). Similarly, 0.005 is the average of 1983q2–1997q3 and 1997q4–2007q4 (from the univariate estimation). That is almost identical to the value obtained for the sub-period of 1983q1–2007q4 (from the multivariate estimation). What that means is that, for the roughly corresponding sub-periods, the estimated values of the intercept are very similar whether they are from the univariate estimation or the multivariate one.

4. Discussion of results

In this study, we explore the possibility of a price convergence in the form of a reduction in regional inflation in the United States in the sense of the purchasing power parity, which is the extended version of the law of one price. If all prices converge to each other, the price dispersion across regions disappears resulting in the same price everywhere. We make use of the standard deviation of regional inflation as the measure of dispersion. As a robustness check, we also experiment with the coefficient of variation for our data to make sure our results are not an artifact of our definition of dispersion. Related to that, we examine the permanency of such a phenomenon, if observed. We do so, by analyzing the behavior of the standard deviation of inflation in a number of regions over time in the USA by employing univariate as well as multivariate models. A particular attention in the multivariate model is devoted to the role of technology. The explanatory variables in the multivariate model are drawn from the quantity theory of money in addition to a technology indicator. Finally, we compare and contrast the results from both models.

After observing a strong correlation between the standard deviation and the coefficient of variation we proceed to our models' findings. In terms of results from our univariate model, we show that the standard deviation of inflation is not constant over time, but we do not necessarily observe an ever-declining pattern. This may point to a persistent inflation dispersion among regions. In other words, we fail to find support for the purchasing power parity for the regions in the USA in our data. This result is consistent with Ellison and Ellison (2009) and Gorodnichenko et al. (2018b) where they find no online law of one price. Non-tradables and implicit contracts between customers and firms may play a role in that outcome (Blinder, 1994; Rotemberg, 2011). Such a phenomenon can cause the persistent short-run real interest rate differentials across regions under the scenario of common monetary policy such as the US (Ogawa & Kumamoto, 2008). In practical terms, it may result in different real interest rates in different regions of the same country.

We try to explore factors causing the non-constant standard deviation of inflation over time with the help of a multivariate model. As indicated above, our multivariate model considers the standard deviation of inflation as a function of the growth of technological innovations, the real GDP gap, and the money growth rate. We find that in the 1971q3–1975q4 sub-period, money growth rate has the biggest impact on the inflation standard deviation in the sense that it reduced the inflation dispersion. In the same period, technological advances played the same role, though to a lower extent. Blinder (1982) describes 1970s as the decade of inflation in the US. Among the explanations of the "Great Inflation" of the 1970s, an excessively expansionary monetary policy was deemed as the root cause of the high inflation (Nelson, 2004). Although Meltzer (2005) extends the Great Inflation period to 1965 to 1984, he, too, emphasizes the role of money in causing high inflation in the USA. Even if these papers do not directly address the price dispersion issue at the time, they all indicate the significance of the lax monetary policy in causing high inflation. Therefore, it makes sense that such a policy would play a substantial role in price dispersion across regions in an era with relatively less technology pervasiveness, at least compared to the modern era. In the next two sub-periods, namely 1976q1–1978q1 and 1978q2–1982q4, the role of technology changes. In the 1976q1–1978q1 sub-period, technology was the biggest reducer of inflation dispersion across regions. However, over the 1978q2–1982q4 sub-period, technology does not seem to have any significant impact on the standard deviation, which we observe as a lull in the power of technology in changing the market behavior regarding inflation. We conjecture that this pattern must be due to the initial adoption of technology, which changed the market first, but then came to a grinding halt as not many new applications of technology were adopted in the market. This is because although initially technology made a splash, there was no noteworthy shift in computing technology until mid-1980s (Jorgenson, 2001; Hilbert & Lopez, 2011). That is why; conventional variables, as suggested by the quantity theory of money, such as the money growth rate had the prominent influence on the inflation variation variable.

Nevertheless, in the longest sub-period of 1983q1–2018q4, technology has not had only a statistically significant effect but also the biggest impact on the standard deviation of inflation. Technology helped reduce inflation differences across regions during that sub-period, more so toward the latter part of this sub-period, that is, 2008q1–2018q4. This must be due to the pervasiveness of information technology. This is consistent with the advanced computing technology of 1980s. On a related note, for a view of the issue from a popular perspective, see Wilson (n.d.) and Alexander (2019). Interestingly enough, the former reference describes 1983 as the birth of the modern era technology. That is why; this is the period when technology plays a noticeable role in the reduction of inflation. On a related note, Lv et al. (2019) find that technology is even more influential on the US inflation than globalization for the 1999–2016 period. Similarly, Wadhwani (2000) predicted a similar impact of technology on the UK inflation for years after 2000. As mentioned before, Yi and Choi (2005) find a negative relationship between inflation and technology pervasiveness in the society where the latter is proxied with the internet use.

One cannot help but notice that this particular sub-period encompasses the recent economic crisis, i.e. the Great Recession. Another way to look at it is that in recent years, technology is so widespread in our everyday lives that the impact of a marginal change (improvement) in technology does not have too much impact on inflation dispersion. Yet, it is not surprising that technology would play a much more pronounced impact on inflation and/or its variation in the future (Ciccarelli & Osbat, 2017; Charbonneau et al., 2017; Hatzius et al., 2017). In the past, any change in technology would have more influence on the way prices are set across the regions. On the other hand, since the price dispersion has not completely disappeared among the US regions, there still must be some impediments precluding markets from attaining perfect competition (Varian, 1980; Zhao, 2006; Gopinath et al., 2011; Dubois & Perrone, 2018; Choi et al., 2019).

Overall, it is fair to say that technology has a great potential in reducing price differences (dispersion) across regions over time. However, this pattern in regional inflation is not uniformly observed over time as other market forces such as the monetary policy may overtake technology in affecting inflation dispersion. Having said that, it is conceivable to think that the technology and technology-based companies such as Amazon are likely to exert a much more pronounced impact on the US market space in the aftermath of the current Covid-19 crisis (Del Rey, 2020). We believe the recent experience of this global pandemic supports that anticipation. Covid-19 has led to far-reaching changes in the everyday life of consumers including shopping habits (Blundell et al., 2020). It is fair to say that the pandemic has caused a structural break in digital market place (Kim, 2020). By forcing people to shop online, the pandemic has compelled consumers to "learn" online shopping, which was long considered an impediment against the digital experience (Peres et al., 2010). Going forward, consumers are highly likely to retain some of the technology based shopping habits that they learn during the lockdowns, and firms will accommodate (Sheth, 2020). Actually, this has been a well-recognized phenomenon in the literature (Rangaswami & Gupta, 2000; Wolfinbarger & Gilly, 2001; Lin & Lekhawipat, 2014). All in all, this points to an ever-expanding digital market exacerbated via the conditions initially imposed by Covid-19. The role of Amazon in the online shopping has significantly increased in the era of the pandemic compared to before. The fact that Amazon has kept hiring while many other companies shed labor is another sign of a healthy growth of the company with a strong hold on the digital marketplace (Del Rey, 2020). We believe the story of Amazon has all the telltale signs portending to a more commanding power of the company. In other words, we conjecture, without analyzing in this paper, that Amazon's leadership in setting prices in the future will rise.

Conclusions

Behavior of prices, and in particular that of inflation, in the modern era of quickly spreading information has been a topic of concern for both researchers and policy makers. The advances in computer and information technology coupled with corporations at whose disposal is the use of such technology should generate "right" conditions for a perfectly competitive market. Argument goes that as price (and by extension, inflation) information spreads quickly and without cost, the market will converge to a zero economic profit situation. If, in fact, such a phenomenon has been materialized, that will have consequences for policy makers, too, especially the central bank. In that case, there will be the same price for any good anywhere (law of one price), or for all goods and services everywhere (purchasing power parity). Obviously, a temporary convergence in prices would have no perpetual impact on the economy; therefore, it is of no concern to monetary policy makers. The permanent change, however, comes with issues for decision makers.

Thus, we investigate such a price convergence in regions of the United States under the guidance of the purchasing power parity and the quantity theory of money extended with the inclusion of technology as an explanatory variable. The standard deviation of inflation is employed as the indication of price dispersion where a mitigating standard deviation is an indication of convergence.

While we observe some signs of a declining price dispersion across regions of the US, we do not find a total disappearance thereof, indicating price barriers across regions. This is an important finding for monetary policy makers since the end result may be different interest rates in different parts of the country.

With the help of the multivariate model, we find that early 1970s' inflation was characterized by the heavy influence of money growth. This is the beginning of a period known as the "Great Inflation." As the pervasiveness of technology increases toward the second half of 1970s, price dispersion moderates. Nevertheless, as the technology induced productivity loses steam we see an inability of technology in contributing to the reduction of price dispersion during late-1970s to early 1980s. Our analysis shows that the impact of technology takes off starting mid-1980s, probably in response to the widespread use of technology in the everyday life. Consumers and corporations have recognized the power of information as communicated by the internet and convenient delivery opportunities, which complement the price information, leading a more uniform pricing scheme across the country, at least compared to previous periods.

As alluded to above, since the price dispersion has not completely disappeared among the US regions, there still must be some impediments precluding markets from attaining perfect competition. Nevertheless, the recent experience of the global pandemic is a candidate to lead the markets more in the direction of digital marketplace. The market-based data gathered so far show that consumers have turned to online environments for shopping purposes, and companies have been accommodating. Amazon, in particular, seems to have captured a significant portion of the online market. Additionally, the marketing literature says that habits learned during crises tend to stick around. Therefore, we think that the price information gathering via online platforms by consumers will only continue to grow. Cognizant of this fact, it is likely that firms will keep an eye on the prices set by competitors. All things considered, we see signs of further price convergence across regions. Having said that, as we do not explicitly address the impact of Covid-19 on prices, we propose this as a subject for future study.

Obviously, these findings should be further investigated with different definitions of technology as the data become more available. After all, the literature is not yet in complete agreement about the measurement of technology (Mincer & Danninger, 2000). Therefore, in conclusion, we guardedly state that information technology has probably led to reduced dispersion in inflation across regions in the USA, but we cannot say that its power is unlimited.

References

Alexander, D. (2019). *7 influential inventions from the 1980s that would go on to change the world*. https://interestingengineering.com/7-influential-inventions-from-the-1980s-that-would-go-on-to-change-the-world

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, *66*, 47–78. https://doi.org/10.2307/2998540

Bai, J., & Perron, P. (2003a). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, *18*, 1–22. https://doi.org/10.1002/jae.659

Bai, J., & Perron, P. (2003b). Critical values for multiple structural change tests. *Econometrics Journal*, *1*, 1–7. https://doi.org/10.1111/1368-423X.00102

Baye, M. R., Morgan, J., & Scholten, P. (2006). Information, search, and price dispersion. In T. Hendershot (Ed.), *Handbook on economics and information systems*. Elsevier. https://doi.org/10.1016/S1574-0145(06)01006-3

Berardi, N., Sevestre, P., & Thébault, J. (2017, June). *The determinants of consumer price dispersion: evidence from French supermarkets* (Banque de France Working Paper No. 632). https://doi.org/10.2139/ssrn.2992468

Blinder, A. S. (1982). The anatomy of double-digit inflation in the 1970s. In R. E. Hall (Ed.), *Inflation: causes and effects* (pp. 261–282). University of Chicago Press.

Blinder, A. S. (1994). On sticky prices: academic theories meet the real world. In G. Mankiw (Ed.), *Monetary policy* (pp. 117–154). University of Chicago Press.

Blundell, R., Griffith, R., Levell, P., & O'Connell, M. (2020). Could COVID-19 infect the Consumer Prices Index? *Fiscal Studies*, *41*(2), 357–361. https://doi.org/10.1111/1475-5890.12229

Brynjolfsson, E., & McAfee, A. (2012, January). *Race against the machine: how the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. The MIT Center for Digital Business.

Castro, J. V. (2004). *Indicators of real economic convergence. A primer* (UNU-CRIS e-Working Papers No. W-2004/2). United Nations University.

Cavallo, A. (2017). Are online and offline prices similar? Evidence from large multi-channel retailers. *The American Economic Review*, *107*(1), 283–303. https://doi.org/10.1257/aer.20160542

Cavallo, A. (2018, September 7). *More amazon effects: online competition and pricing behaviors* (Working Paper). Harvard Business School & NBER. https://doi.org/10.3386/w25138

Charbonneau, K., Evans, A., Sarker, S., & Suchanek, L. (2017). *Digitalization and inflation: a review of the literature. Staff analytical note/note analytique du personnel 2017-20*. Bank of Canada.

Choi, B., Kim, D., & Cho, H. C. (2019). Price response, information, and asymmetry of price dispersion. *Applied Economics*, *51*(39), 4270–4281. https://doi.org/10.1080/00036846.2019.1591600

Ciccarelli, M., & Osbat, C. (Eds.). (2017). *Low inflation in the euro area: causes and consequences* (ECB Occasional Paper No. 181). European Central Bank (ECB), Frankfurt a. M. https://www.econstor.eu/bitstream/10419/154634/1/ecbop181.pdf

Clemente, J., Montanes, A., & Reyes, M. (1998). Testing for a unit root in variables with a double change in the mean. *Economics Letters*, *59*(2), 175–182. https://doi.org/10.1016/S0165-1765(98)00052-4

Del Rey, J. (2020, April 10). Amazon was already powerful. The coronavirus pandemic cleared the way to dominance. *Vox*. https://www.vox.com/recode/2020/4/10/21215953/amazon-fresh-walmart-grocery-delivery-coronavirus-retail-store-closures

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*, 427–431. https://doi.org/10.1080/01621459.1979.10482531

Dubois, P., & Perrone, H. (2018). *Price dispersion and informational frictions: evidence from supermarket purchases* (Discussion Paper Series – CRC TR 224, Discussion Paper No. 047, Project B 04). University of Bonn.

El-Arian, M. (2019, May 24). How the Amazon-Google-Uber effect dictates low inflation. *The Guardian*. https://www.theguardian.com/business/2019/may/24/how-the-amazon-google-uber-effect-dictates-low-inflation

Ellison, G., & Ellison, S. F. (2009). Search, obfuscation, and price elasticities on the internet. *Econometrica*, *77*(2), 427–452. https://doi.org/10.3982/ECTA5708

eMarketer Editors. (2018, July 16). *Amazon now has nearly 50% of US ecommerce market*. https://www.emarketer.com/content/amazon-now-has-nearly-50-of-us-ecommerce-market

Federal Reserve Bank of San Francisco. (2019, July 24). *San Francisco Tech Pulse* [*SFTPINDM114SFRBSF*]. FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/SFTPINDM114SFRBSF

Federal Reserve Bank of St. Louis. (2018, April 3). A closer look at the reasons for low inflation. *St. Louis Fed on the Economy blog*. https://www.stlouisfed.org/on-the-economy/2018/april/closer-look-reasons-low-inflation

Federal Reserve Bank of St. Louis. (2019, July 25). *NBER based recession indicators for the United States from the period following the peak through the trough [USRECQ]*. https://fred.stlouisfed.org/series/USRECQ

Fishman, C. (2007). *The Wal-Mart effect* (2nd ed.). Penguin Books.

Goodfriend, M. (2002). The phases of U.S. monetary policy: 1987 to 2001. *Economic Quarterly*, *88*(4), 1–17.

Goolsbee, A. D., & Klenow, P. J. (2018, May 18). *Internet rising, prices falling: measuring inflation in a world of e-commerce* (Working Paper). University of Chicago. https://doi.org/10.3386/w24649

Gopinath, G., Gourinchas, P.-O., Hsieh, C.-T., & Li, N. (2011). International prices, costs, and markup differences. *American Economic Review*, *101*(6), 2450–2486. https://doi.org/10.1257/aer.101.6.2450

Gordon, R. J. (2014, August). The turtle's progress: secular stagnation meets the headwinds. *VOX / CEPR Policy Portal*. https://voxeu.org/article/turtle-s-progress-secular-stagnation-meets-headwinds

Gorodnichenko, Y., Sheremirov, V., & Talavera, O. (2018a). Price setting in online markets: does it click?" *Journal of the European Economic Association*, *16*(6), 1764–1811. https://doi.org/10.1093/jeea/jvx050

Gorodnichenko, Y., Sheremirov, V., & Talavera, O. (2018b). The responses of internet retail prices to aggregate shocks: a high-frequency approach. *Economics Letters*, *164*, 124–127. https://doi.org/10.1016/j.econlet.2018.01.014

Hatzius, J., Phillips, A., Mericle, D., Hill, S., Struyven, D., Reichgott, K., & Thakkar, A. (2017, August). US daily: the internet and inflation: how big is the amazon effect? (Mericle). *Goldman Sachs Economics Research*.

Hilbert, M., & Lopez, P. (2011). The world's technological capacity to store, communicate, and compute information. *Science*, *332*(6025), 60–65. https://doi.org/10.1126/science.1200970

Hodrick, R. J., & Prescott, E. C. (1997). Postwar U.S. business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, *29*, 1–16. https://doi.org/10.2307/2953682

Isaac, A. (2018, July 9). 'Amazon effect' on prices to be included in official inflation statistics. *The Telegraph*. https://www.telegraph.co.uk/business/2018/07/08/amazon-effect-prices-included-official-inflation-statistics/

Jorgenson, D. W. (2001). Information technology and the U.S. economy. *The American Economic Review*, *91*(1), 1–32. https://doi.org/10.1257/aer.91.1.1

Kim, R. Y. (2020). The impact of COVID-19 on consumers: preparing for digital sales. *IEEE Engineering Management Review*, *48*(3), 212–218. https://doi.org/10.1109/EMR.2020.2990115

Lampertius, J. (2019, April 8). *The Amazon effect on physical retailers: how not to end up like sears.* https://www.mytotalretail.com/article/the-amazon-effect-on-physical-retailers-how-not-to-end-up-like-sears/

Lin, C., & Lekhawipat, W. (2014). Factors affecting online repurchase intention. *Industrial Management and Data Systems*, *114*(4), 597–611. https://doi.org/10.1108/IMDS-10-2013-0432

Lv, L., Liu, Z., & Xu, Y. (2019). Technological progress, globalization and low-inflation: evidence from the United States. *PLoS ONE*, *14*(4), e0215366. https://doi.org/10.1371/journal.pone.0215366

Meltzer, A. H. (2005). Origins of the great inflation. *Review*, *87*(2, Part 2), 145–176. https://doi.org/10.20955/r.87.145-176

Microdinc. (n.d). *What is the Amazon effect*. https://www.microdinc.com/blog/what-is-the-amazon-effect/

Mincer, J., & Danninger, S. (2000, July). *Technology, unemployment and inflation* (Working Paper No. 7817). NBER. https://doi.org/10.3386/w7817

Nelson, E. (2004). *The great inflation of the seventies: what really happened?* (Working Paper No. 2004-001). Federal Reserve Bank of St. Louis. https://doi.org/10.20955/wp.2004.001

Ogawa, E., & Kumamoto, M. (2008, July). *Inflation differentials and the differences of monetary policy effects among euro area countries* (Working Paper No. E-9). Tokyo Center for Economic Research. http://www.tcer.or.jp/wp/pdf/e9.pdf

Pan, X., Ratchford, B. T., & Shankar, V. (2004). Price dispersion on the internet: A review and directions for future research. *Journal of Interactive Marketing*, *18*(4), 116–135. https://doi.org/10.1002/dir.20019

Peres, R., Muller, E., & Mahajan, V. (2010). Innovation diffusion and new product growth models: a critical review and research directions. *International Journal of Research in Marketing*, *27*, 91–106. https://doi.org/10.1016/j.ijresmar.2009.12.012

Rangaswami, A., & Gupta, S. (2000). Innovation adoption and diffusion in the digital environments: some research opportunities. In V. Mahajan, E. Muller, & Y. Wind (Eds.), *New product diffusion models*. Springer.

Rotemberg, J. J. (2011). Fair pricing. *Journal of the European Economic Association*, *9*(5), 952–981. https://doi.org/10.1111/j.1542-4774.2011.01036.x

Russell, T., Fischer, P., Behlke, M., & Quinn, K. (2018). The Amazon effect on public finance: what is the optimal tax structure in the internet age? *Municipal Finance Journal*, *39*(1/2), 39–63.

Satterthwaite, F. E. (1946). An approximate distribution of estimates of variance components. *Biometrics Bulletin*, *2*(6), 110–114. https://doi.org/10.2307/3002019

Sheth, J. (2020). Impact of Covid-19 on consumer behavior: Will the old habits return or die? *Journal of Business Research*, *117*, 280–283. https://doi.org/10.1016/j.jbusres.2020.05.059

Varian, H. R. (1980). A model of sales. *The American Economic Review*, *70*(4), 651–659.

Wadhwani, S. (2000, May). The impact of the internet on UK inflation. *Bank of England Quarterly Bulletin*, 184–198. https://ssrn.com/abstract=764267

Welch, B. L. (1951). On the comparison of several mean values: an alternative approach. *Biometrika*, *38*(3–4), 330–336. https://doi.org/10.1093/biomet/38.3-4.330

Wilson, W. (n.d.). *Proof that 1983 was the birth of modern era technology*. https://www.goliath.com/tech/proof-that-1983-was-the-birth-of-modern-era-technology/

Wolfinbarger, M., & Gilly, M. C. (2001). Shopping online for freedom, control, and fun. *California Management Review*, *43*(2), 34–55. https://doi.org/10.2307/41166074

Yi, M. H., & Choi, C. (2005). The Effect of the Internet on Inflation: Panel Data Evidence. *Journal of Policy Modeling*, *27*, 885–889. https://doi.org/10.1016/j.jpolmod.2005.06.008

Zhao, Y. (2006). Price dispersion in the grocery market. *The Journal of Business*, *79*(3), 1175–1192. https://doi.org/10.1086/500673

Zivot, E., & Andrews, D. (1992). Further evidence of great crash, the oil price shock and unit root hypothesis. *Journal of Business and Economic Statistics*, *10*, 251–270. https://doi.org/10.1080/07350015.1992.10509904