Quality of Goods and Price Setting

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Abstract:

We investigate whether quality of product affects price setting behaviour by employing a unique monthly-frequency dataset which contains prices of 861 central processing unit (CPU) during April 2009 - August 2013. These data are merged with CPU performance scores for each precisely identified product. Our results suggest that quality of goods plays an essential role in online price setting. In particular, the product's quality is positively associated with the frequency of price change and synchronisation rate of price changes across sellers within product, and negatively correlated with the size of price changes. Therefore, the increase in product's quality should lead to more price flexibility and less price dispersion. Our findings suggest that it is necessary to dig deeper on sources of price rigidity and price dispersion as quality of goods is often not included into modelling.

JEL classification: E31, L11, L81, L86

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1. Introduction

Answering the question "How do sellers set the price for their products?" is vital not only for microeconomic but also can help us to answer some long-standing macroeconomic questions. Particularly, we know that money policy is a main tool, which every government uses to intervene in the market and orientate the economy. However, its effectiveness mainly depends on the flexibility of the price. If the price is easy to change, the effects of an increase in money supply would be absorbed by price changes.

In order to measure the level of price flexibility, there are numerous studies have attempted to investigate price setting behaviours, such as how often the seller changes the price and how much do they change? They have found various evidences of price frictions to support for the idea of a model with sticky price. These frictions can appear in several forms such as, search costs (Burdett & Judd, 1983; Benabou, 1988), costs of nominal price adjustment (Sheshinski and Weiss, 1977; Reinsdorf, 1994), transportation/delivery costs (Betancourt and Gautschi, 1993), as well as managerial costs such as costs of collecting information, decision-making, and communication (Zbaracki et al., 2004). Those existing literatures have contributed to create a sturdy foundation for price setting activities in the markets.

Nevertheless, there are still some remaining questions that only receive limited attention of researchers. For example, the universal perception of high quality – high price suggests us that quality of products could have effects on sellers' decision to set prices. Additionally, the quality changes bias, which is caused by the improvement in quality of goods, is still the largest source of measurement error in inflation assessment. It was recognised and mentioned in a number of previous studies, either conventional market data or online market data are used (see for example, Shiratsuka, 1999; Bils, 2009; Cavallo and Rigobon, 2016).

Apparently, product's quality is an important factor that may play some roles in price setting activities, thus, have potential effects on the level of price stickiness. Consequently, quality could also affect price dispersion as price stickiness is considered as a major cause of price dispersion in previous literatures. However, to the best of my knowledge, due to the difficulties in quality measurement, none of existing literatures obtains a precise measure for quality of goods. Thus, quality is still absent in most of studies. This remaining problem can be enlightened by studying that long-standing omitted factor with a more precise measure for the product quality. Our paper aims to fill the gap in existing literatures by using a unique feature in the dataset, which is the performance score, as a proxy to measure product's quality.

We first attempt to answer the question: “Does quality of goods matter in price setting activities?”. Then, we relate the quality of goods to some important factors of market operation (such as the frequency and size of price changes, the level of price synchronisation within a good across sellers and within a seller across goods) to shed some light in the facts of price setting activities as well as price rigidity and price dispersion measures. Finally, we use goods quality to improve the accuracy in computation of traditional economic indicators.

In this paper, our main concern is the quality factor, hence, we investigate the price setting of central processing unit (CPU) on online-market because of two main reasons. Firstly, CPU is a special product that can help us to avoid the difficulties of quality measurement that previous studies have. For example, wine has a huge issue of measuring its quality that make the quality does not have any significant effects on the market price (Combris et al., 2003). This is the consequence of the differences in tastes between customers. Regarding to CPU, its performance can be measured precisely by several technical tests, which are developed by leading technology companies. A performance score can fully reflect the quality of a CPU as the perceived quality of customer when buying a CPU is nearly the same and mainly come from the performance but rarely come from other factors, such as sensory or outlook characteristics. Secondly, we use prices on online market to minimise several price frictions. Online market has unique characteristics, which are different with standard markets, for example low search costs, not depend on physical location, and insignificant costs of price changes. Therefore, investigating price setting behaviour online offer an exceptional opportunity to eliminate those frictions and quality should be directly reflected by prices. In addition, gathering prices data on e-commercial market is less costly and more convenient than on conventional market but still has a reasonably high quality (e.g. Cavallo et al., 2016; Gorodnichenko and Talavera, 2017).

Our unique dataset contains price for CPU on the United States online market, which is precisely identify at product level by the manufacture product numbers. It covers monthly prices of total 861 CPUs sold across 218 online retailers for a 53 month-period between April 2009 and August 2013. We define an observation by its manufacturing product number, identifications of sellers (seller ID) and month. In total, our dataset contains 100,703 CPU – seller – month price quotes. Importantly, this paper has the CPUs’ performance scores thus, contrarily to previous studies, we can determine and research the prices relevant to quality of goods.

Using our comprehensive and representative dataset, we found significant evidences of the important role that product quality plays in price setting activities. Particularly, the increase in product quality is associated with the increase in frequency and decrease in size of price setting. We also found that quality of goods has positive relationship with the degree of synchronisation across sellers. As a result, it has a negative relationship with the degree of price stickiness and price dispersion. This result is consistent with the predictions of models with price stickiness and suggests that quality of goods does play some roles in price setting. Hence, it might have significant effects on the measures of both price stickiness and price dispersion. However, our dataset only obtains price data for only one type of product – CPU on online market in the US and we only have the proxy to measure the quality of CPU. Measurement of quality for several types of products is still a challenge that is unsolved. This fact calls for more research to dig deeper into products' quality – the omitted variable in the existing literature, in order to have more precise estimations of price rigidity and price dispersion measures as well as other economic indicators.

The structure of the rest of our paper is as follows. Section 2 is dedicated to describing the data. Section 3 provides the estimations and the regression results of the frequency and size of price adjustments together with the estimates of synchronisation rate of price changes. Section 4 investigates characteristics of price dispersion. Finally, our conclusion is given in Section 5.

2. CPU data description

2.1. Data collection

This paper uses a comprehensive and representative dataset, which includes two parts: CPUs' price quotes on United States e-commercial market and performance scores data for each CPU model.

The first part of our dataset contains CPU-Seller's price quotes. We use an identifier, which is a unique manufacturing product number (MPN), for each CPU model listed online by US sellers. For instant, MPN "BX80601940" uniquely identifies Intel Core i7-940 2.93GHz Processor. Similarly, we have unique identifications to identify sellers (seller ID). These data are gathered from a leading price comparison website (PCW) that provides price quotes for US online market. Particularly, at midnight on the first day of each month, a Tcl/Python script starts automatically to download webpages with price quotes. After that, we extract information of MPNs, sellers' IDs and prices for each CPU – Seller quotes. Note that the prices including in our dataset is net prices, which are the prices before taxes and shipping fees. Additionally, different from a number of existing papers, which only obtain less than 12 months of data (see for example Lünnemann and Wintr, 2011), we exploit the advantages of a longer time series dataset, which covers for 53 months, to achieve results that are more accurate.

The second part of our dataset contains a unique feature, which no other studies has employed, it is the performance scores for CPUs. We use it as a proxy to measure precisely the quality of goods since CPU is a special commodity that consumers' perceived quality mainly come from CPUs' performance. These data are provided by a leading authority specialises in software and hardware performance benchmarking and testing, which is a Microsoft Partner and Intel Software Partner. This company also owns one of the world's largest CPU benchmark website. They not only donated the final scores of CPU's performances but also provided us all the test results, which are used to compute the performance marks. Furthermore, their testing methods and models to produce the CPU's performance score are published on their website. Therefore, if they change their performance measure in the future, we still can produce new performance scores and update our data to be comparable with new CPU models.

2.2. Data filters and quality

Because quality measure for goods is vital in our study, we dropped CPUs that do not have performance scores after merging two parts of our dataset. All used or refurbished CPU's prices was removed as well as their price are not comparable with the price of new CPU. In addition, to minimise the effects of extreme values in our data, we dropped for both the top and the bottom 1 percent of the prices. For time series analyses, we only keep CPUs with more than 20 observations; and CPU with at least three sellers to calculate the duration it stayed on the market.

After applying all filters above, our large sample covers monthly prices of total 861 CPUs sold across 218 online retailers in the United States for a 53 month-period from April 2009 to August 2013. We define an observation by its MPN, seller ID and month. Totally, our dataset contains 100,703 observations.

One may concern about the quality of prices data on PCWs since it does not directly come from sellers. The price on PCWs maybe not up to date or discrepant from sellers' real prices if sellers only post low prices on PCWs to attract customers, then, switch the prices. In fact, online merchants have incentives to keep updating their latest prices on PCWs since they usually have to pay for clicks on those webpages. Therefore, if their prices are not up to date, they will not gain sales and waste their money. Similar to our dataset, Gorodnichenko, Sheremirov and Talavera (2018) gathered price data from PCWs and found some differences between PCWs price and price on seller's websites. However, the price quotes are still remarkable consistent between two sources with a high correlation ($\rho = 0.98$). Additionally, they found sufficient evidences that price data from PCW is consistent with Bureau of Labour Statistics (BLS) data and updated rapidly in response to an aggregated shock. Hence, the price data from PCWs have rationally high quality.

2.3. Notation and Aggregation

In this paper, we use p_{ist} to stand for the prices of CPU *i* sold by seller *s* at time *t* and q_i stand for the performance score of CPU *i*. Thus, we have the set of all CPUs, sellers and time as $\mathcal{C}$ = {1, …, C}, $\mathcal{S}$ = {1, …, S}, $\mathcal{T}$ = {1, …, T}, respectively. In which C is the total amount of CPUs, S is the total amount of sellers and T is when the period ends. Time measurement is month. The subscripts *i*, *s* and *t* is corresponding to a given model of CPU, seller or time. For example, C_{st} is the total number of CPU, which are offered by seller *s* at time *t*, while S_{it} represents the total number of sellers that sell CPU *i* at time *t*. The letter with a bar means the average, such as $\bar{p}_{it}$ is the average price of CPU *i* across all sellers offer it at time *t*.

We use performance scores to measure accurately the goods' quality, at least partially filling the gap in existing literatures, which do not have such feature. After randomly comparing the scores of CPU performance in our data with other well-known CPUs benchmarking websites, we did not find any conflicts in the results. To highlight the differences between this paper with its exclusive quality measure and previous researches, we employ two different aggregate measures for frequency, size and synchronisation rate of price adjustments over CPUs and sellers. Firstly, we calculate the raw average, which is $\bar{f}$ (unweighted mean). Secondly, we compute the aggregate across sellers that sold a CPU to collapse our data to goods level. Then we employ the performance weighting scheme to produce the average over CPUs, which we call $\overline{f^b}$. We refer $\overline{f^b}$ to between CPUs weighting. For instant, if f_{is} is the frequency of price adjustments for CPU *i* sold by seller *s*, and q_i is the performance score of CPU *i*. Those two aggregated measures have formula as:

$$\bar{f} = \sum_i \frac{1}{C} \sum_s f_{is} \frac{1}{S}$$

$$\overline{f^b} = \sum_i \frac{q_i}{\sum_i q_i} \sum_s f_{is} \frac{1}{S} \tag{1}$$

2.4. Price distribution and performance

Table 1 shows the average price of each percentiles of the distribution over products ($\bar{p}_i$), the mean and standard deviation of the average log price ($\overline{log\ p_i}$), within the sample. Overall, the median CPU in our data cost £193.97 and 25% of CPUs have their price under £98.35; CPU that is more expensive than £334.65 is accounted for top 25% highest prices of the sample. After applying the performance weighting scheme to calculate the between CPUs weighting estimation, the average price of the median CPU increases by more than 50% to £299.69. Thus, the more powerful a CPU is, the more expensive it could be.

[Table 1]

In order to investigate the essential of performance in the price measurement, for each CPU we calculate the average of the differences in the whole period between log price of a CPU i, which is $log(p_{ist})$ and the log of median price across CPUs at a given time, which is $log(\tilde{p}_{st})$. The formula is:

$$\bar{p}_{is} = \frac{1}{T} \sum_t [log(p_{ist}) - log(\tilde{p}_{st})] \tag{2}$$

Figure 1(a) illustrates the density of the deviations without weights and with the between CPUs weights based on the performance scores, q_i. The grey dashed line presents the distribution of the log price deviation from the median across CPUs, and the black solid line presents the performance-weighted distribution of that deviation. We can see that applying the performance weights make the distribution shift to the right. This graph imply that the CPU, which has performance score significantly higher than the median CPU score, is more expensive.

Figure 1(b) shows the relation of prices and performance scores by plotting CPU performance against prices. Similar to figure 1(a), we measure price and performance by the log-deviation from the median CPU for a seller on a given month. The dots show data points averaged within bins based on 99 percentile levels of the log-deviation of price from one to ninety-nine percentiles. Then, we present a Lowess smoother to show nonlinearities relation in the performance–price relationship. The Lowess smoothing is computed with a 0.1 bandwidth.

[Figure 1]

In order to show another aspect of the relationship between performance and price of CPU, we divided our sample into 4 different quartile groups of CPUs base on their performance scores and 4 other groups base on their prices namely upper quartile, upper middle quartile, lower middle quartile and lower quartile of performance or price. It can be seen in figure 2(a) that the average price of each CPU group depends on its performance quartile: the better the performance score is, the higher the average price of a group. In addition, the price of the high-end CPUs has wider fluctuations, while low-end CPU only has small changes in their average price over the period. Although average price of all 4 groups were fluctuated throughout the whole period but then in the end they came back to their initial price level after 53 months.

It is also interesting to point out that, despite that the average price of four quartile groups of performance returned to their initial levels in the end of the period, the rating scores of all 4 quartile groups of price increased rapidly (Figure 2(b)). The significant improvement of CPU's performance is a clear evidence of the amazing speed of the technology innovation. As a result, the prices of old CPU models should decrease when there are new and more efficient CPUs appear. Additionally, the increasing speed of all quartile's performance score was almost equal. It might imply that technology companies do not only focus to develop the most powerful CPUs for high-end customers, but they also invest their resources to improve CPU's quality in all class of performance for difference customer segmentation.

[Figure 2]

3. Price Stickiness in CPU price setting

In several macroeconomic models, price stickiness is a vitally important factor of the monetary policy transmission mechanism. Numerous studies have attempted to measure the rigidity of the price and investigate its properties (for example, Bils and Klenow, 2004; Boivin, Giannoni and Mihov, 2009; Midrigan, 2011; Nakamura and Steinsson, 2013; Ellison, Snyder and Zhang, 2018). They have found many types of price-adjustment frictions that cause price become inflexible. However, on online market, we may expect to find a smaller price-change friction than what we witnessed in conventional market because of the features of e-commerce, such as small nominal price change costs, small searching costs and small monitoring competitors' prices costs (Ellison and Ellison, 2005). In other words, the frequency and size of price adjustments on e-commercial should be larger and smaller, respectively, than they are in traditional market. This section aims to contribute to existing literature by providing some more empirical evidences of these facts on US online CPU market by taking the quality of goods into consideration.

3.1. Regular and Posted Prices

Regarding to Nakamura and Steinsson (2008), temporary sales have an important role in generating price flexibility. Similarly, Klenow and Malin (2010) argue that temporary price changes (sale-related price changes) do not wash out with aggregation and each model of "sales" have different implication for measuring stickiness level of price. On the other hand, Eichenbaum, Jaimovich and Rebelo (2011) and Kehoe and Midrigan (2015) reached a consensus that aggregate price is still sticky even when the posted price changes regularly. In line with that, Dhyne et al. (2006) stated that it is more appropriate to analyse regular price changes than focus on sales for the investigation of price flexibility at an aggregate level. Therefore, in this paper, we distinguish between posted prices (the prices that include in our dataset) and regular prices (the prices that exclude temporary changes) and report both results.

We do not have sales flag as in scanner data such as BLS. Thus, following previous studies (for example, Nakamura et al., 2008; Chahrour, 2011; Kehoe et al., 2015; Gorodnichenko et al., 2018), we identify temporary sales by "sales filter", which is the ∨-shape or ∧-shape in price changes. Particularly, we consider an increase or decrease in price as temporary price change if the price returns to its previous price level within one month.

The monthly frequency and size of sales in our data is shown in table 2. We found that the mean and median frequency of sales in column (1) and (3) equal to 1.85% and 0.68%, respectively. The median size of sales is 2.71% (see column (4)). We focus more on CPUs that have higher quality by applying performance weights and found the sales appear more often, the mean and median of frequency jump to 2.31% and 1.84%, respectively. Nevertheless, the median size of sales drop to 2.44%.

[Table 2]

In addition, we present the level of synchronisation of sales across CPUs for a given seller and across sellers for a given CPU, which can provide useful information of sales' characteristics. We compute the synchronisation rate across sellers equal to the average percentage at a time of sellers, who have sales on a specific product, when a seller has sales on the same CPU. Say A represents the number of sellers that offer CPU *i* at time *t*, who have temporary price changes; and B represents the total number of sellers that offer CPU *i* at time *t*. The synchronisation rate is:

$$\frac{A-1}{B-1}$$

Note that, this ratio is computed monthly and limited to the CPU that is sold by at least two sellers (B ≥ 2) and at least one of its sellers has sales (A ≥ 1). The level of synchronisation ranges from zero (no synchronisation) to one (perfect synchronisation). If the synchronisation rate is low, the implication could be sales are strategic substitutes: a seller gains less from sales if at the same time other sellers are also having sales on the same product (see for example Klenow et al., 2010; Guimaraes and Sheedy, 2011). Contrarily, a high synchronisation level might imply that sales are strategic complements. Similarly, we define the synchronisation rate of sales across CPUs that are sold by a seller as the proportion of CPUs sold by that seller, which are on sales together at month *t*.

The results in Table 3 show that the monthly synchronisation rate of sales across sellers within a CPU has the mean equal to 2.34% (see column (1)) and we do not observe synchronisation in over half of the sellers (see column (3)). The mean of synchronisation of sales across CPUs is 6.10%, which is significantly higher than that ratio across sellers. Hence, it is more likely that a seller will put sales on a CPU when he has sales on other CPUs than when other competitors have sales on the same product. However, we can say this degree of synchronisation of sales is still low, since it is similar to the average frequency of sales.

[Table 3]

3.2. Frequency and Size of Price Changes

3.2.1. Frequency of Price Changes

Following previous studies (for example Bils et al., 2004; Nakamura et al., 2008), we determine the frequency of price adjustment as the proportion of non-zero price changes to the total number of price changes observed within our dataset. Particularly, we consider a price change that is smaller than 0.1% as a zero-price change, which mean it is not counted as non-zero price change. In other words, if we use $\varphi_{ist} = \mathbb{I}\{q_{is,t} > 0\}\,\mathbb{I}\{q_{is,t-1} > 0\}$ to identify a price adjustment that is observed (for both zero and non-zero price changes); the number of observed price adjustment per CPU-seller quote is $\prod_{is} = \sum_t \varphi_{ist}$; the conditional function of a non-zero change is $\chi_{ist} = \mathbb{I}\{|\Delta \log p_{ist}| > 0.001\}$. Hence, the formula of frequency of a CPU sold by a seller is:

$$f_{is} = \frac{\sum_t \chi_{ist}}{\prod_{is}} \tag{3}$$

After that, we collapse the result to CPU level by computing the raw average frequency, $\bar{f_\iota}$, for each CPU, which has more than four observations for a price change as follow:

$$\bar{f_i} = \frac{1}{\sum_{s\in\mathcal{S}_i}\mathbb{I}\{\prod_{is}>4\}} \sum\nolimits_{s\in\mathcal{S}_i} f_{is}\mathbb{I}\{\prod_{is} > 4\} \tag{4}$$

Then, we produce the no weights average ($\bar{f}$) and between CPU weights average ($\overline{f^b}$) for both posted and regular price changes frequency, which is reported in table 4, as below:

$$\bar{f} = \sum\nolimits_{i\in C} \frac{1}{\mathrm{C}} \sum\nolimits_{s\in\mathcal{S}_i} f_{is}\mathbb{I}\{\prod_{is} > 4\} * \frac{1}{\sum_{s\in\mathcal{S}_i}\mathbb{I}\{\prod_{is}>4\}} \tag{5}$$

$$\overline{f^w} = \sum\nolimits_{i\in C} \frac{q_i^{\prod}}{\sum_i q_i^{\prod}} \sum\nolimits_{s\in\mathcal{S}_i} f_{is}\mathbb{I}\{\prod_{is} > 4\} * \frac{1}{\sum_{s\in\mathcal{S}_i}\mathbb{I}\{\prod_{is}>4\}} \tag{6}$$

Lastly, we compute the implied duration of price spell as:

$$\bar{d_\iota} = -\frac{1}{\ln(1-\bar{f_i})} \tag{7}$$

Table 4 reports the median of the frequency of posted price adjustment is 41.65% and the implied duration is 1.86 months, correspondingly, when no weights are applied (see column (1)). When we use the one-month sales filter to compute the same statistic for regular price, the median frequency drops by more than 4% to 37.28% and the implied duration raise to 2.14 months. Then, we use the performance weights between CPUs to compute the frequency of price adjustments for both posted and regular prices and found that they both rise to 44.87% and 39.75%, respectively. As a result, the implied duration of price spells drops to the range between 1.68 and 1.97 months.

Our results show the price spells of CPU online stores in the US is up to 2.14 months, which is shorter than the results reported in previous studies for other segments on online market (such as Lünnemann et al., 2011; Boivin, Clark and Vincent, 2012). Nonetheless, prices of CPU on e-commercial market is still not completely flexible.

[Table 4]

3.2.2. Size of Price Changes

Using the same symbols in the notation part, our formula to calculate the average absolute size of price adjustment for CPU *i* is:

$$\overline{|\Delta\, log\, \rho_i|} = \frac{1}{\sum_{s\in\mathcal{S}_i}\sum_t \chi_{ist}} \sum_{s\in\mathcal{S}_i}\sum_t |\Delta\, log\, \rho_{ist}| \cdot \chi_{ist} \quad (8)$$

Then, we calculate the raw average size of price adjustments ($\overline{|\Delta\, log\, p|}$) and apply the between CPU weighted scheme to calculate the between CPU weighted average of size ($\overline{|\Delta \log p|}^w$).

The last line of each panel in table 4 presents the median absolute size of price adjustment. The results for posted prices and regular prices are similar, 7.59% and 7.86%, respectively. However, when we employ performance weights the size varies from 5.06% to 5.16%. These results are smaller than the results of Gorodnichenko et al. 2018, which also reported for US online market but has a wider range of products.

3.3. Synchronisation

In order to investigate at which level different sellers change their prices simultaneously, we define the synchronisation rate across sellers as the average proportion of sellers, who adjust their prices for a given CPU, when a seller has changed the price of the same CPU. We use A to denote the number of sellers that change their price for CPU *i* at month *t*; B to denote the total number of sellers that sell CPU *i* at month *t*, the synchronisation rate therefore is $\frac{A-1}{B-1}$. In which, there is at least one seller change the price of CPU *i* (A>0) and the number of sellers that sell CPU *i* is greater than one (B>1). Using our notation similar to previous section, we have $\chi_{ist} = \mathbb{I}\{|\Delta \log p_{ist}| > 0.001\}$ as the indicator function of a price adjustment of CPU *i* sold by seller *s* at month *t* and $S_{it} = \#\mathcal{S}_{it} \leq S$ is the number of seller offer CPU *i* at time *t*. Our formula of monthly synchronisation rate across sellers, z_{it}, for CPU *i* as time average of non-missing value is:

$$z_{it} = \frac{\left(\sum_{s \in \mathcal{S}_{it}} \chi_{ist}\right) - 1}{S_{it} - 1} \quad (9)$$

Then we compute the non-weighted average synchronisation rate, in which all products have the same weights. In order to examine the effects of products' quality, we calculate the average with performance weights for each CPU, where the weights are:

$$W_i = \frac{q_i}{\sum_i q_i}$$

Table 5 shows the synchronisation rates of price adjustments across CPUs and across sellers for both posted and regular prices. The mean and medium of synchronisation rates across sellers is quite high, ranging from 31.71 to 33.99 and 32.92 to 36.08, respectively, depends on whether it is calculated with or without sales filter. This result for across CPUs synchronisation rate is even higher (more than 40%). Note that our results is the degree of monthly synchronisation so it is still comparable with the results (normally range around 10% to 15%) of previous papers that calculated this ratio by weekly (for example Gorodnichenko et al. 2017, 2018).

[Table 5]

3.4. Predictors of price stickiness

The features of market and goods might have relation with the heterogeneity of price stickiness across goods. In this paper, we focus on four variables namely: (1) number of sellers that sell a given good, (2) quality of goods, (3) the median price, (4) the percentage of price quotes that end at 95-99 cents ("price points"), (5) The stability of sellers for a given good and (6) the number of products that has higher or lower quality enter or exit the market in the life time of a given good. The first variable might illustrate market competition. The second variable could reflect goods' characteristic. The third one might be a proxy for the returns of buyers' search. The fourth one could reflect the level of inattention to prices when choosing between products (e.g. Knotek II, 2011). The fifth variable, stability of sellers is the proxy for the turnover of sellers. Lastly, the changes of product's quality in the market is measured by the number of products that have better or worst performance than a given CPU enter and exit the market.

We estimate the pricing moment including the frequency, size, and synchronisation rates across sellers at product level. In this study, we compute our left-hand side variables, for instant frequency of price change, as raw average for a specific product of each seller with no weights. After that, we collapse the data to product level by taking the raw average across sellers to use as a dependent variable and run the regression with no weights.

Table 6 report our results of regression for all dependent variables. Firstly, our results suggest that a market with more sellers, which means it is a more competitive market, should have less price stickiness, such as price changes occur more often and have smaller size; the synchronisation rate of price changes across sellers, should be higher. These results are consistent with previous empirical studies (e.g. Gorodnichenko et al., 2018). Secondly, quality of goods in the market have significant effects on all of our dependent variables. In particular, market contains more high-quality products should have higher and smaller frequency and size, respectively, of price adjustments; and higher synchronisation rate across sellers. Hence, an increase in quality of goods in the market should yield more prices' flexibility. Thirdly, the market, which has higher proportion of price points, should expect to have more sticky prices (price changes occur less often and lower synchronisation rate across sellers). This might imply that bounded rationality could have some roles in price rigidity. Fourthly, a higher degree of the stability of sellers, which means that the more difficult to enter the market, could lead to a higher level of price stickiness. Lastly, the increase in the number of better-quality products enter the market could cause the price become less sticky. Summarily, we come to the conclusion that features of online markets, for example competitive level, quality of goods in the market, the share of price points and the changes of product quality in the market have significant effects on the level of price stickiness.

[Table 6]

4. Price dispersion

Price dispersion, under macroeconomic perspective, refers to a vital factor, which is useful in explaining the causes of price stickiness. Also, price rigidity is often considered as a key cause of price dispersion. By examining price dispersion, we might obtain significant implication for the welfare computation, the design of optimum policies and the nature of competition (see Woodford, 2011; Sheremirov, 2015).

Numerous researches have paid their attention to price dispersion but mainly on conventional market (such as Dahlby and West, 1986; Bernabou, 1992; Borenstein and Rose, 1994; Kaplan and Menzio, 2015). However, the number of studies that investigate the properties of price dispersion on online market is still limited and only examine in some specific markets due to the constraint of accessing to the data. Although e-commerce has special characteristics that can minimise the effects of price frictions, earlier papers still found significant evidences of price dispersion on online market (such as Chevalier and Goolsbee, 2003; Baye, Morgan and Scholten, 2004; Gorodnichenko et al., 2017)

In this section, we extend the literature by including an important factor that is often omitted in previous studies - quality of products into the computation of price dispersion among CPU retailers on US online market.

4.1 Intra-month dispersion across sellers

This section report the coefficient of variation (CV) and standard deviation of the monthly log prices since they are the most commonly reported measures in earlier studies of price dispersion. Together with that, we also generate other measures for price dispersion such as the value of information (VI), which equal to the log difference of the average and the lowest price; interquartile range (IQR); Range, which is the gap between the lowest and highest log price; Gap, which is the difference between the two lowest log prices.

First, we calculate the measure of price dispersion between sellers for an identified CPU in a month, then collapse our data to product level by taking the time averages. Finally, we apply weighting schemes to calculate the non-weighted average and the performance-weighted average across products. Since the frequency of our monthly sales is quiet small, which is up to 2.31% (see table 2), the results for price dispersion is nearly the same between regular prices and posted prices. Therefore, we only report the results of posted price in table 7.

[Table 7]

As we can see in table 7 above, in general, all the measure of price dispersion decrease when the performance-weighting scheme is applied. The CV is roughly 25% and significantly drop to 17.33% when we apply performance weights (see column (1)) and the results of standard deviation of log prices is similar to the results of CV (see column (2)).

One might argues that the observed price dispersion is caused by the distinction in the shopping experience of customer among sellers (see Stigler, 1961). This differences is not likely to be significant when customers shopping online as consumers only deal directly with a seller after completing the transaction. In order to fully solve this potential problem, we follow Gorodnichenko et al., 2018 to employ the regression below:

$$log\ \mathrm{p_{ist}} = \alpha_\mathrm{i} + \gamma_\mathrm{s} + \varepsilon_\mathrm{ist} \tag{10}$$

Where α_i and γ_s control for product and seller fixed effects, respectively. The dispersion of the residuals (ε_ist) gives us the price dispersion net of sellers' heterogeneity in, for example, shipping costs, return policies, which are likely to remain unchanged in a short time (see Nakamura et al., 2008). We can employ seller fixed effects to capture the differences in reputation, delivery conditions, and return costs amongst sellers.

The results in table 7 column (7) show the residual price dispersion is 21.72 log points when no weights are applied. Once we use performance weights, it fall to 14.3 log points.

4.2 Predictors of price dispersion

Previous literatures often explain the price dispersion existence by three main causes, which are search costs, frequency of price changes – the channel in price stickiness models (the difference in prices exist since the price changes are set at different time), and price discrimination (see for example Coibion, Gorodnichenko and Hong, 2015; Sheremirov, 2015). In order to document these sources of price dispersion, we employ the regression of the standard deviation of the log prices on a number of variables, which measure price stickiness, market size, stability of sellers, and return to search. Due to the similarity between non-weighted and performance-weighted results, we only report the performance-weighted results in table 8.

[Table 8]

In table 8, we report the results for the regression of standard deviation of log price in column (1) and the regression results after removing seller fixed effects in column (2). We found that the quality of products does have significantly negative effect on the measure of price dispersion in both before and after removing sellers fixed effects. Additionally, the share of convenient prices, and the frequency of sales are negatively associated with price dispersion. Meanwhile, we found the absolute size of regular price changes positively affect the level of price dispersion. The results are similar between the regression before and after removing seller fixed effects.

Regarding to models with price stickiness, an increase in level of price stickiness should generate a higher level of price dispersion. Thus, we should expect the factors, which are associated with more flexible prices, have negative effects on price dispersion, and vice versa. Since we found a positive relation between product's quality and price flexibility (price changes more frequently and have smaller size), the quality improvements should decrease the price dispersion. Table 8 shows a consistent result with the forecasts of models with price stickiness: price dispersion has negative relation with goods quality and positive relation with size of regular price changes. However, the negative relationship between share of convenient prices with both level of price flexibility and level of price dispersion does not support for the prediction of price stickiness model. Moreover, we found evidences that are not supportive for the models with search costs since a higher product price, which measures the search returns, is correlated with a higher level of price dispersion.

5. Conclusion

The data of CPU prices on online market provides an exceptional chance to dig deeper into the absent factor in existing literatures – product's quality. The prices on Internet are more convenient to collect and CPU's quality is easier to measure. This research exploit the opportunity by using a precise measure for the CPU's performance to enlighten about the role of quality in price setting and its impact on the degree of price stickiness and price dispersion.

Through the use of our unique and comprehensive data, which not only covers a broader period of time but also provides a unique feature to measure product quality - CPU performance, we find that the quality of goods indeed does affect price setting on online market. Market contains more high-quality products should have price changes more often with smaller size, and a higher synchronisation rate across sellers. As a result, an increase at aggregate level in products' quality in the market should lead to a lower level of price stickiness and smaller price dispersion. Moreover, we found evidences support for the results of Gorodnichenko et al. (2018), a more competitive market should have less price stickiness. In addition, the market with higher proportion of price points should expect price to change less often and have lower synchronisation rate across sellers but also decrease the price dispersion level. This might indicate that bounded rationality could have some roles on the level of price rigidity and price dispersion. Furthermore, our result support for the prediction of model with price rigidity: a larger size of regular price adjustment is associated with higher degree of price dispersion. However, the evidences of the negative influences of share of convenient prices on both price flexibility and price dispersion does not consistent with the implication of price rigidity models. We also found that a higher level of sellers' stability lead to a higher level of price stickiness but does not have significant impact on price dispersion after we remove the seller fixed effects. Finally, we suggest that it is possible and necessary to take goods quality into modelling in order to improve the precision in measurement of traditional economic indicators.

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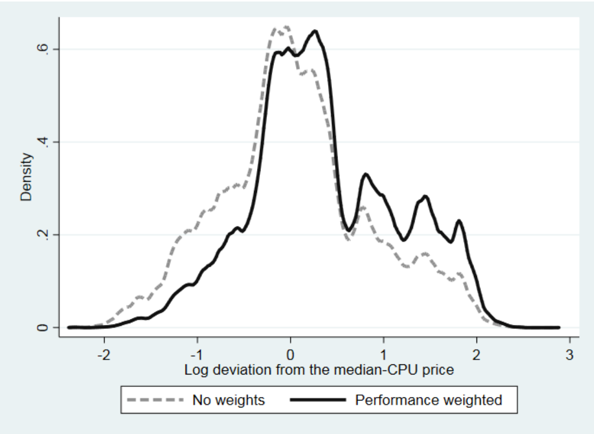
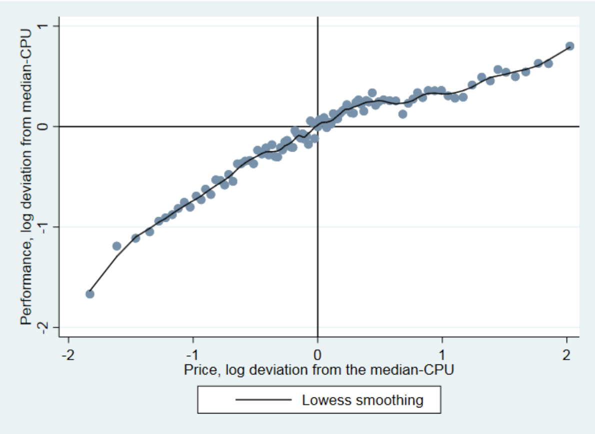
Figures and Tables.





(a) (b)

Figure 1. Prices and Performances' log deviation from median distribution.

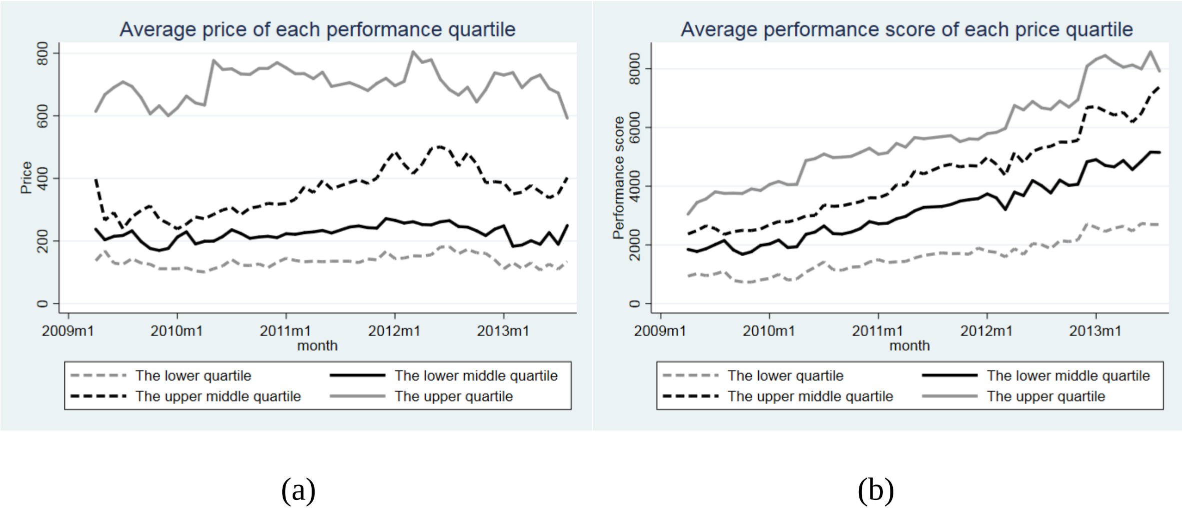


Figure 2. Price and Performance by quartiles.

Table 1. Descriptive statistics for prices, USD.

	Mean Log Price		Mean Price, percentile					
	Mean (1)	SD (2)	5% (3)	25% (4)	50% (5)	75% (6)	95% (7)	N (8)
No weights	5.22	0.89	51.57	98.35	193.97	334.65	1051.30	861
Performance weighted	5.74	0.86	81.90	186.49	299.69	602.37	1502.68	

Note: Column (1) and (2) present the mean and standard deviation of the average log price for a CPU ($\overline{log\ p_i}$); column (3)-(7) present the mean price for each percentile of the CPU's price ($\bar{p}_i$); column (8) shows the total number of products, N.

Table 2. Monthly frequency and size of sales.

	One-month filter				
	Mean Frequency (1)	SD Frequency (2)	Median Frequency (3)	Median Size (4)	N (5)
No weights	1.85	3.39	0.68	2.71	575
Performance weighted	2.31	3.05	1.84	2.44	

Note: Column (1) shows the monthly average of sales frequency across CPUs (%). Column (2) reports the standard deviation of sales frequency across CPUs. Column (3) shows the median CPU's frequency of sales. Column (4) shows the absolute size of sales for the median CPU, in which the absolute size of sales equal to the gap between the log of sales price and the log of regular price (multiple by 100). Column (5) shows the number of CPUs. A sales is identified by using the one-month, two-sided sales filter.

Table 3. Monthly synchronisation rate of sales.

	Synchronisation across sellers			Synchronisation across CPUs		
	Mean (1)	SD (2)	Median (3)	Mean (4)	SD (5)	Median (6)
No weights	2.34	4.26	0.00	6.10	11.72	3.13
Performance weights	2.72	4.48	1.47	6.57	12.13	3.56

Note: Column (1) – (3) show the mean, standard deviation and median of monthly synchronisation rate in sales for a CPU across Sellers. Column (4) – (6) report the same statistics of the monthly synchronisation rate for a seller across CPUs. A sales is identified by using the one-month, two-sided sales filter.

Table 4. Monthly frequency and size of price changes.

	No weights (1)	Performance weighted (2)
Posted price		
Median Frequency, %	41.65	44.87
Implied duration, months	1.86	1.68
Median absolute size, log points	7.59	5.06
Regular price		
Median Frequency, %	37.28	39.75
Implied duration, months	2.14	1.97
Median absolute size, log points	7.86	5.16

Note: Column (1) shows the raw frequency and size of price adjustment when missing values was excluded. Column (2) shows those results after applied performance weighting scheme. We compute the regular prices based on a one-month, two-side sales filter.

Table 5. Monthly synchronisation rate of price changes.

	Synchronisation across sellers			Synchronisation across CPUs		
	Mean (1)	SD (2)	Median (3)	Mean (4)	SD (5)	Median (6)
Posted price						
No weights	33.99	20.61	36.08	46.04	29.32	42.86
Performance weights	37.40	17.18	38.69	47.69	27.44	43.88
Regular price						
No weights	31.71	20.26	32.92	44.07	29.08	41.58
Performance weights	34.27	17.04	34.15	45.18	27.22	42.86

Note: Column (1) – (3) present the mean, standard deviation and median of monthly synchronisation rate in price changes for a CPU across Sellers. Column (4) – (6) present the same statistics of the monthly synchronisation rate for a seller across CPUs. We compute the regular prices based on a one-month, two-side sales filter.

Table 6. Predictor of posted-price stickiness.

	Frequency of Price changes, %	Absolute size of price changes, log points	Synchronisation across Sellers, %
Predictors	(1)	(2)	(3)
Ln Number of Seller	-0.30	-4.40***	-0.33
	(0.50)	(0.30)	(0.56)
Ln Performance scores	17.99***	-7.19***	13.52***
	(1.74)	(1.32)	(2.31)
Ln Median Price	-2.02	4.06	-8.91
	(4.63)	(3.39)	(5.97)
Ln Median Price squared	-0.32	-0.32	0.14
	(0.43)	(0.31)	(0.55)
Share of Price Points	-12.18***	0.51	-10.03***
	(1.44)	(1.18)	(2.18)
Stability of sellers	-32.54***	-0.71	-9.40**
	(3.14)	(2.16)	(3.87)
Ln number of higher CPU enter	8.35***	-1.79*	4.38***
	(1.38)	(0.95)	(1.66)
Ln number of lower CPU enter	-1.83	-0.62	0.69
	(1.12)	(0.82)	(1.44)
Ln number of higher CPU exit	-0.08	-0.71	0.40
	(0.80)	(0.56)	(0.97)
Ln number of lower CPU exit	1.63	0.48	3.34**
	(1.27)	(0.93)	(1.66)
R^2	0.32	0.17	0.16
N	3930	3597	3439

Note: This table shows the results of the regression of the frequency in column (1), size in column (2) and synchronisation rate across sellers in column (3) on the quarterly posted price adjustment on the set of dependent variables above. The measures of price stickiness are unweighted. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 7. Average dispersion of posted price across sellers.

	CV (1)	Std(log p) (2)	VI (3)	IQR (4)	Range (5)	Gap (6)	Std(ε) (7)	N (8)
No weights	24.98	25.88	26.94	36.59	51.35	26.04	21.72	739
Performance weights	17.33	17.22	18.30	22.66	40.73	13.93	14.30	

Note: Column (1) – (7) report the average dispersion of posted prices measured with: the coefficient of variance (CV), which is computed as the standard deviation divided to the mean (in %); std(log *p*), which is the standard deviation of the log price; value of information (VI), which is computed as the log difference between the average and the minimum price; interquartile range (IQR) equal to the log difference between the 75th and 25th percentile; range is the log difference between the highest and lowest price; gap is the log difference between the two lowest prices; and std(ε), in which ε is the error term in the regression of log *p* on good and seller fixed effects; respectively, for CPU online-market in the US. Column (8) shows the number of products in the sample.

Table 8. Predictors of posted price dispersion

Predictors	Standard deviation of log price (1)	Net of seller fixed effects (2)
Log number of sellers	0.51	0.75
	(0.96)	(0.74)
Ln Performance scores	-3.23**	-4.79***
	(1.38)	(1.07)
Log median price	0.39	1.95***
	(0.81)	(0.63)
Share of Price Points	-9.07*	-8.76**
	(5.28)	(4.09)
Frequency of Regular Price changes	0.11	0.04
	(0.08)	(0.06)
Absolute Size of Regular Price changes	1.17***	0.94***
	(0.10)	(0.07)
Frequency of sales	-0.20	-0.09
	(0.13)	(0.10)
Absolute size of sales	-0.04	-0.09
	(0.08)	(0.06)
Synchronization of posted price changes	-0.13*	-0.04
	(0.08)	(0.06)
Seller stability	17.34*	1.16
	(10.09)	(7.81)
R^2	0.65	0.74
N	317	317

Note: This table shows the results of the regression of the standard deviation of log price in column (1), and the regression results after removing seller fixed effects in column (2) on the set of dependent variables above. All the reported variable in this table are unweighted. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.