Shocks vs Responsiveness: What Drives Time-Varying Dispersion?

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Abstract

The dispersion of many economic variables is countercyclical. What drives this fact? Greater dispersion could arise from greater volatility of shocks or from agents responding more to shocks of constant size. Without data separately measuring exogenous shocks and endogenous responses, a theoretical debate between these explanations has emerged. In this paper, we provide novel identification using price data in the open-economy environment: using confidential BLS microdata, we document a robust positive relationship between exchange rate passthrough and the dispersion of item-level price changes. We then show that this relationship supports models with time-varying responsiveness.

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1 Introduction

The cross-sectional dispersion of many economic variables is countercyclical, but there is much debate over the source of this empirical phenomenon.[1] This is because existing research measures the dispersion of *endogenous* variables, which will reflect some combination of exogenous shocks and firms' optimal responses to those shocks. As such, greater dispersion of endogenous outcomes could occur if exogenous shocks get bigger (what we refer to as greater volatility) but also if firms respond more to shocks which are the same size (what we refer to as greater responsiveness).[2]

With only data on outcomes and not the separate contributions of exogenous shocks and endogenous responses, a theoretical debate between these explanations has emerged. Many models such as Bloom et al. (2012) and Vavra (2014) assume that firms draw exogenous idiosyncratic shocks with time-varying volatility in order to generate time-variation in dispersion. On the other side of the debate, papers such as Bachmann and Moscarini (2012), Ilut et al. (2014), Baley and Blanco (2016) and Munro (2016) propose a varied set of mechanisms such as learning, ambiguity aversion, incomplete information and customer search to generate variation in dispersion through the responsiveness channel. Making empirical progress on this debate is important since exogenous changes in volatility have been proposed as a possible source of business cycles. If time-varying dispersion is driven in part by time-varying responsiveness, then ignoring variation in responsiveness will lead one to overstate the size of exogenous volatility shocks.

Making empirical progress distinguishing time-varying responsiveness from time-varying volatility is difficult, but we show that the open economy environment can be used to provide identification in the price-setting context. This is because it provides a large and observable cost shock, the nominal exchange rate, which can be used to differentiate these channels. In the first half of the paper, we use confidential BLS import price data to document that item-level price change dispersion is both countercyclical and highly correlated with exchange rate passthrough. In the second half of the paper, we use a workhorse open-economy model to show that these facts support an important role for time-varying responsiveness in explaining price behavior. The intuition is straightforward: increasing responsiveness increases both dispersion and passthrough. In contrast, when volatility increases, dispersion increases but passthrough actually declines as price changes become dominated by idiosyncratic forces. While this does not necessarily rule out the presence of some time-variation in volatility, it does imply that quantitatively significant time-variation in responsiveness is necessary for this model to match the empirical behavior of prices and thus reduces the inferred size of volatility shocks necessary to match the data.[3]

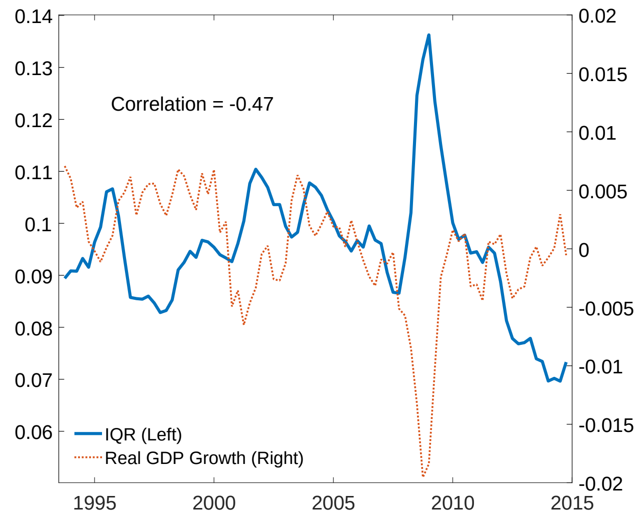
In more detail, our paper proceeds in three steps. First, we start by documenting new facts. We begin by showing that, like many other economic outcomes, the dispersion of item-level price changes in BLS import price data is strongly countercyclical. For example, Figure 1 shows that the interquartile range (IQR) of price changes in our data moves substantially across time and exhibits a negative correlation with real GDP growth. Second, the dispersion of price changes is highly correlated with exchange rate passthrough. To illustrate this simply, we divide our entire sample into 8-month long windows and

[1]Countercyclical dispersion is found in Bloom (2009) (sales growth), Bloom et al. (2012) (revenue TFP and employment growth), and Vavra (2014) (prices). Bachmann and Bayer (2014) finds procyclical dispersion of investment rates, but as we discuss in footnote 18, this is highly consistent with our results since their measure includes zeros.

[2]To avoid confusion, we distinguish between "dispersion" and "volatility" throughout the paper. We define dispersion as the spread of endogenous outcome variables, while volatility is the spread of exogenous shocks.

[3]Our estimated model actually rejects the presence of any significant volatility shocks.

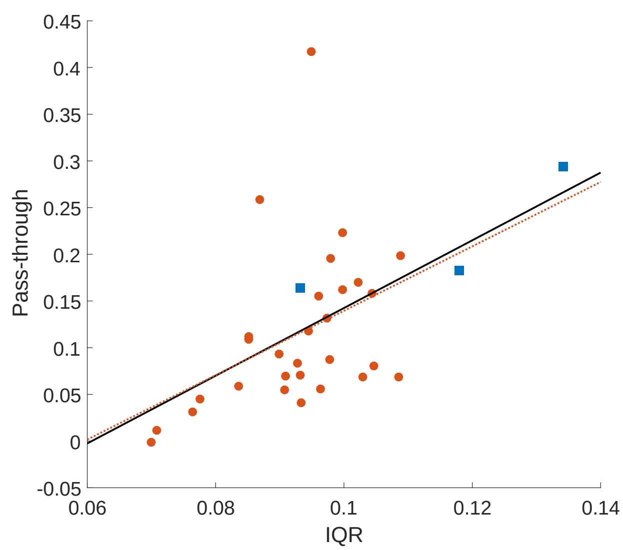
Figure 1: Price Change Dispersion is Countercyclical



This figure shows the IQR (75-25 range) of all non-zero price changes in our benchmark sample, described below, and chained real GDP growth from 1993m10 to 2015m1. The monthly IQR is averaged quarterly for consistency with GDP measures, and both series are smoothed with a 3-period moving average.

compute the IQR of price changes and our preferred measure of exchange rate passthrough separately in each window.[4] The resulting scatter plot of IQR vs. passthrough in Figure 2 shows the strong positive relationship between these variables. Since the time-series graph in Figure 1 shows that the IQR in the Great Recession is an outlier, we include Great Recession observations separately as blue squares in Figure 2 to show that the passthrough-IQR relationship is not driven by this single recession.

Figure 2: Dispersion vs. Passthrough



This figure shows the IQR of all non-zero price changes against our preferred measure of exchange rate passthrough, described below. Both statistics are computed separately in a series of 8-month disjoint windows which span our sample period. Windows which have a majority of months during the Great Recession, as defined by NBER, are shown in blue. The black regression line includes all observations while the red-dotted line excludes Great Recession observations. The regression with all observations has a slope coefficient of 3.625, t-stat of 3.36 and R^2 of 0.27.

[4] Appendix Figure A.1 shows similar patterns hold for different window lengths.

This positive relationship between price change dispersion and passthrough is very robust. It is not driven by changes in the frequency of price adjustment, secular trends, changes in exchange rate volatility, by particular products or countries, or by mechanical reverse causation, and it holds under a variety of alternative specifications designed to deal with certain misspecification concerns.[5] We also show that the positive relationship between dispersion and passthrough holds after controlling for various business cycle indicators and at the sector-level after controlling for time dummies to flexibly absorb common aggregate variation. Finally, similar results arise at the individual item level: items which exhibit disperse price changes across time also exhibit high exchange rate passthrough when they change prices. Together these results allay concerns about spurious correlation and effects of confounding aggregate shocks.

If one views exchange rate passthrough as a simple reduced form measure of responsiveness, our empirical results then suggest an important link between countercyclical dispersion and responsiveness. However, such "suggestive" evidence should be viewed with caution. While passthrough is a widely computed moment in the open-economy literature, interpreting this moment and its relationship with dispersion requires imposing additional structure.[6]

In the second part of the paper, we move in this direction by adopting the flexible price framework of Burstein and Gopinath (2014). In this model, the mapping from structural parameters to observables is straightforward, which allows us to illustrate the basic nature of the identification problem as well as its solution. With flexible prices, the dispersion of price changes across firms is determined by two parameters: i) the volatility of idiosyncratic shocks and ii) the response of optimal prices to shocks. This means that changes in dispersion could be explained by changes in either parameter. However, these parameters have very different implications for exchange rate passthrough. Increasing volatility increases price change dispersion but has no effect on passthrough, since optimal passthrough is scale-invariant.[7] In contrast, increasing responsiveness simultaneously increases dispersion *and* passthrough. Thus, in this simple flexible price environment, changes in responsiveness can explain the positive relationship between dispersion and passthrough observed in the data, while changes in volatility cannot.

In the final part of the paper, we turn to a quantitative environment with more realistic pricing frictions. This is important because price rigidities are important in our data and their presence complicates the simple mapping from structural parameters to observables. However, we show that price frictions actually amplify our previous conclusions: while increases in responsiveness continue to increase both dispersion and passthrough, increases in volatility increase dispersion but lead to a counterfactual decrease in passthrough. This is because when the volatility of idiosyncratic shocks increases, exchange rate movements become less relevant for optimal price adjustment and measured passthrough declines.[8]

In addition, this quantitative model provides a laboratory which we use to explicitly test the validity of our earlier empirical methodology. In particular, there are valid concerns that our empirical patterns might be driven by censoring, small samples, sample turnover, or misspecification. We address these

[5] In particular, one might be concerned that this positive correlation reflects mechanical reverse causality whereby increases in passthrough make prices more sensitive to exchange rate shocks and increase price change dispersion. However, we show in our quantitative results that this mechanical effect on variance is negligible.

[6] See e.g. Burstein and Gopinath (2014) for a detailed discussion of the mapping between passthrough regressions and a variety of commonly used models of incomplete passthrough as well as associated pitfalls.

[7] That is, doubling the size of a cost shock doubles the optimal price change.

[8] More formally, as we show in section 3.2 state-dependent pricing implies an upward statistical "selection bias" in our exchange rate passthrough regression since firms are more likely to adjust when the exchange rate and idiosyncratic shock reinforce each other. As idiosyncratic volatility rises, this bias declines and our measure of passthrough falls.

concerns head-on by formally estimating our quantitative model using indirect inference to match our empirical regressions. In doing so, we simulate data from our model, replicate BLS sampling and run regressions on this simulated data identical to those in our empirical work. This indirect inference estimation procedure allows us to rule out many potential concerns with our empirical results, since the same biases should arise when running regressions on simulated and actual data. Put differently, as usual with indirect inference, identification does not require our empirical regressions to be correctly specified or have any structural interpretation in the true model. It merely requires that changes in structural parameters manifest themselves distinctly in our reduce form regressions, and this is indeed the case.

What does variation in responsiveness represent? As described above, a variety of mechanisms can endogenously generate countercyclical dispersion. In Appendix B, we show that forces in these models all map to the same responsiveness parameter that is key to our qualitative results. This means that our empirical strategy cannot differentiate between these models of time-varying responsiveness, but this also means that our *qualitative* insights do not require taking a stand on a particular model of responsiveness.

Moving from qualitative results to quantitative results necessarily comes with some tradeoff: in order to formally estimate our model and reach conclusions about magnitudes, we must impose more structure on the data generating process. Since it is infeasible to simultaneously include all potential mechanisms that can generate countercyclical responsiveness, we focus solely on variation in responsiveness which arises from movements in the "super-elasticity" of demand in Kimball's preferences.[9] We focus on this source of responsiveness shocks for three reasons: 1) This is a standard specification in the open economy literature for generating incomplete passthrough, which has been used to rationalize a number of related cross-sectional passthrough facts. It is important that matching our new facts not come at the cost of missing existing results. 2) It is parsimonious and straightforward to solve numerically. The full version of our quantitative model includes four aggregate and two idiosyncratic states and requires global solution methods in an equilibrium environment, so estimation would be infeasible in more complicated settings such as those with learning and incomplete information. 3) It fully nests existing models in the literature, such as Vavra (2014), which explain countercyclical dispersion via countercyclical volatility, and so it gives these models equal footing in matching our new empirical evidence.

It is difficult to directly assess the plausibility of our estimated super-elasticity shocks, since no empirical estimates of this statistic exist. However, we show that these relatively simple shocks produce observable series which are quite reasonable in many dimensions. In particular, after picking exchange rates in our model to match data from 1993-2015, we show that we are able to well-match the behavior of the IQR, overall inflation, import inflation, output growth and adjustment frequency over our 1993-2015 sample with only super-elasticity and nominal demand shocks. The model also matches time-series variation in exchange rate passthrough which is not directly targeted, and it generates markup movements across time which are relatively small and within the range of estimates in the literature. Thus, we conclude that even though super-elasticity movements cannot be directly measured in the data, such shocks produce reasonable results along observable dimensions.

It is important to note that our analysis focuses on import prices and we have no data on quantities, so one should be cautious when extrapolating to other contexts. However, several recent papers reach similar conclusions in other environments and suggest that our conclusions indeed have some measure of

[9] That is the elasticity of the elasticity of demand with respect to a firm's relative price. See Klenow and Willis (2006) for the first use of this terminology.

external validity. First, Fleer et al. (2015) extends our analysis from imports to broader consumer prices in Switzerland and finds similar results. Moving beyond prices to real outcomes, Ilut et al. (2014) shows that individual firms' employment responds more to idiosyncratic TFP changes during recessions, and Decker et al. (2016) shows that secular reallocation trends in US manufacturing are driven by changes in responsiveness rather than changes in the volatility of shocks. Finally, a growing literature argues for cyclical changes in market structure and demand which should lead to exactly the sort of time-varying responsiveness necessary to explain our results.[10]

Our paper is related to some recent empirical work trying to determine if aggregate volatility is a source of, or response to, business cycles. These papers study aggregate time-series volatility rather than cross-sectional dispersion, and so they use identification strategies which focus on relationships between aggregate variables. This makes them quite distinct from our micro data based strategy.[11] For example, Baker and Bloom (2013) uses natural disasters to instrument for stock market first and second moments in order to assess their independent effects on GDP growth, and Ludvigson et al. (2016) and Berger et al. (2016) use time-series VAR strategies to explore similar questions of causality.

Within the passthrough literature, we are most closely related to Gopinath and Itskhoki (2010). We focus on time-series variation in passthrough and explore its link to the dispersion of price changes while their paper focuses on long-run differences in passthrough across different items and links this to the frequency of price adjustment. Our focus on time-series variation leads us to alternative empirical specifications better suited for this purpose as well as to the estimation of a model with a variety of aggregate shocks. Nevertheless our results are broadly complementary, and we ultimately find that similar structural forces can help to jointly explain both their cross-sectional and our time-series evidence.

2 Empirical Results

2.1 Data Description

We now briefly describe the data used in our analysis.[12] We use confidential import price micro data for detailed items collected monthly by the Bureau of Labor Statistics from October 1993-January 2015. The target universe of the price index consists of all U.S. imports. An "item" in the data set is defined as a unique combination of a firm, a product and the country of origin. An example of the type of item in our data is "Lot # 12345, Brand X Black Mary Jane, Quick On/Quick Off Mary Jane, for girls, ankle height upper, TPR synthetic outsole, fabric insole, Tricot Lining, PU uppers, Velcro Strap."[13]

Prices are collected for approximately 10,000 imported items using voluntary confidential surveys.[14] The BLS collects "free on board" (fob) prices at the foreign port of exportation before insurance, freight or duty are added, and almost 90% of U.S. imports have a reported price in dollars. Respondents are asked for prices of actual transactions that occur as close as possible to the first day of the month.

[10]See e.g. Stroebel and Vavra (2016), Munro (2016) and Kaplan and Menzio (2016).

[11]Bachmann et al. (2016) explore a useful related micro exercise looking at the behavior of investment expectation errors, but since investment is highly endogenous their evidence cannot distinguish changing responsiveness from changing volatility.

[12]See Gopinath and Rigobon (2008) for more detailed data description. This data has also previously been used by Gopinath et al. (2010), Gopinath and Itskhoki (2010), Neiman (2010), Berger et al. (2012) and Berger and Vavra (2017).

[13]This example is taken from Gopinath and Rigobon (2008).

[14]As with all surveys, there are some concerns about data quality, but Gopinath and Rigobon (2008) uses the 2001 Anthrax scare as a natural experiment to argue for accuracy. Furthermore, we have explore measurement error in our quantitative environment and found that it, if anything, attenuates the empirical relationships we document.

We focus on a subset of the data that satisfies the following three criteria: 1) We restrict attention to market transactions and exclude intrafirm transactions, as we are interested in price-setting driven by market forces.[15] 2) We require that a good have two price changes during its life so that we can measure passthrough of cumulative exchange rate movements over a completed spell into the item's new price.[16] 3) We restrict attention to imports whose prices are invoiced in dollars rather than in foreign currency. We use data from all countries and all products, however we exclude commodities since these items have little market power. We restrict attention to dollar-priced items, so as to focus on the relationship between dispersion and passthrough after removing variation due to currency choice. Gopinath et al. (2010) has shown large differences in passthrough across goods invoiced in different currencies, but the vast majority of products in the database are invoiced in dollars rather than foreign currency.

Overall these sample choices conform with the now large literature studying exchange rate passthrough from a micro perspective. In Appendix A we provide further statistics on the properties of our benchmark sample and additional information on each cut of the data. More importantly, we show that our results are robust to a variety of alternative sample selection criteria.

2.2 Measuring Dispersion and passthrough

Our primary dispersion measure is the interquartile range (IQR) of all non-zero log price changes in a given month. IQR is robust to outliers and has been widely used in the literature, but we show throughout that all results are similar when using other measures of dispersion such as the standard deviation of price changes. Since this dispersion measure varies across months as the distribution of price changes moves, we refer to it as "month-level dispersion".[17] Measuring dispersion excluding zeros helps to isolate mechanical effects of frequency from changes in the price change distribution conditional on adjustment, and is ultimately crucial for identification.[18] More specifically, since the frequency of adjustment is low, increases in frequency lead to increases in the dispersion of price changes inclusive of zeros. This is true even if adjusting prices always change by the same amount. Measuring dispersion excluding zeros and frequency separately allows us to explore their independent relationships with passthrough.

Our benchmark exchange rate passthrough measure is what Gopinath and Itskhoki (2010) call medium-run passthrough (MRPT), which measures the share of exchange rate movements passed through into an item's price after one price adjustment. Specifically, we estimate the regression on adjusting prices:

$$\Delta p_{i,t} = \beta \Delta e_t + Z'_{i,t}\gamma + \epsilon_{i,t}. \tag{1}$$

Here, $\Delta p_{i,t}$ is item i's log price change, Δe_t is the cumulative change in the bilateral exchange rate since item i's last price change, and $Z'_{i,t}$ is a vector of item and country level controls.[19] We estimate this

[15] Neiman (2010) shows that passthrough depends on whether transactions take place within or between firms.

[16] Some alternative passthrough specifications we explore allow us to relax this requirement and it does not change our results. We also show that all results are robust to only including items with many price changes.

[17] We focus on month-level dispersion, but we also document that similar dispersion-passthrough relationships hold across items by calculating what we call "item-level" dispersion: the standard deviation of all non-zero price changes for a particular item across time. We use the standard deviation since items typically have a small number of price changes.

[18] See Bachmann and Bayer (2014) for related discussion. They show that the standard deviation of investment rates including zeros is procyclical while the standard deviation conditional on "spike" adjustment is countercyclical. This difference is driven by changes in the frequency of adjustment spikes. Overall, their conclusions are highly consistent with other patterns of counteryclical dispersion and could similarly be driven by either changing volatility or responsiveness.

[19] As usual, there are some concerns about interpreting exchange rate movements as exogenous, which is one reason for

regression with country and sector fixed effects.[20] The coefficient β measures the fraction of cumulated exchange rate movements "passed-through" to an item's price when adjusting.[21]

While many passthrough measures exist in the literature, our choice of MRPT which conditions on price adjustment is crucial for our identification strategy. As we show in more detail in Section 3.2 one cannot differentiate movements in responsiveness from movements in volatility using unconditional passthrough measures. This is because if one includes zeros when measuring passthrough, then changes in the frequency of adjustment in response to changes in volatility and responsiveness confound identification. This does not imply that MRPT is the "best" measure of passthrough in general or that it is most relevant statistic for all passthrough related questions, but it is particularly useful for our goal of differentiating movements in responsiveness from movements in volatility.

The results from estimating average passthrough for the entire sample using (1) are shown in Column 1 of Table 1. Consistent with prior literature, we find that average MRPT is low. When a price changes, it passes through only 0.154% of a 1% change in the nominal exchange rate.[22]

2.3 Baseline Results

Figure 1 shows that price change dispersion varies substantially across time. However, as discussed above, it is impossible to tell from Figure 1 whether this variation is driven by changes in the volatility of exogenous shocks or in the endogenous responsiveness to those shocks. We now document the central empirical fact of our paper: time periods with greater price change dispersion also exhibit greater exchange rate passthrough. To test for a time-series relationship between price change dispersion and MRPT we begin by splitting our sample into quintiles by the value of IQR_t and then estimate equation (1) separately using only observations in each quintile. Figure 3 shows that passthrough more than quadruples from the lowest quintile of month-level dispersion to the highest quintile.[23]

Of course, the months in each IQR bin differ from each other in many ways besides their month-level dispersion. To what extent is the positive relationship between passthrough and dispersion correlated with changes in other observables? To explore this, we move from binned regressions to a more structured regression that interacts exchange rate movements with dispersion which we use to show that the positive dispersion-passthrough continues to hold after controlling for a wide variety of time-varying covariates.[24] In particular, we begin by running the following regression:

$$\Delta p_{i,t} = \beta_0 \Delta e_t + \beta_1 IQR_t \times \Delta e_t + \lambda IQR_t + Z'_{i,t}\gamma + +\epsilon_{i,t}, \tag{2}$$

where all variables are defined as in Regression (1). Table 1 Column (2) shows regression results with no additional covariates. Consistent with Figure 3, an increase in IQR is associated with a large increase in

including controls for macro conditions. In addition, we are mainly interested in the relative ranking of passthrough across firms and time-periods rather than the absolute level, so endogeneity is less of a concern.

[20] The sector fixed effects are at the primary strata lower (PSL) level, defined by the BLS as either the 2 or 4-digit harmonized tariff code. The other baseline controls are U.S. GDP and CPI and foreign country CPI.

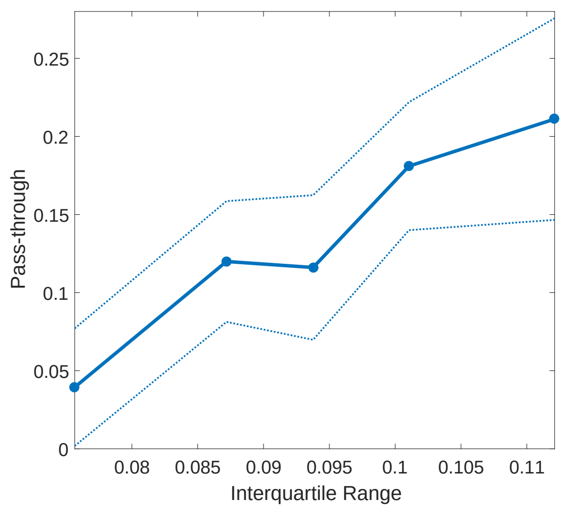
[21] Holding frequency constant, a decline in β implies real exchange rates move more strongly with nominal exchange rates.

[22] Existing papers typically find passthrough coefficients closer to 0.24. Our slightly lower number is due to the use of bilateral exchange rates, all countries rather than OECD countries, and the use of a moderately longer sample. Using trade-weighted currencies and OECD countries increases MRPT to close to 0.3.

[23] Figure A.2 in Appendix A.1 shows that estimating this binned-passthrough relationship more non-parametrically using 100 overlapping bins produces very similar results.

[24] Since IQR and many other controls are endogenous, results show conditional correlations rather than causal relationships.

Figure 3: Dispersion vs. Passthrough



This figure shows separate estimates of regression (1) in each of 5-quintiles by the value of IQR_t. All regressions have country × PSL fixed effects and robust standard errors are clustered at the country × PSL level. We also include controls for foreign CPI growth, US gdp growth and US CPI growth. 95% confidence intervals are shown with dotted lines, and the average IQR value in each quintile is shown on the x-axis.

passthrough. To ease interpretation, coefficients in all tables are standardized, so the 0.07 coefficient on $IQR \times \Delta e$ means that a one standard deviation increase in IQR is associated with a seven percentage point increase in MRPT. This is a substantial effect relative to average passthrough of 14.3% given by the coefficient on Δe. For example, it implies that a 10% exchange rate increase during a month at the 5th percentile of IQR will lead adjusting prices to increase by an average of only 0.3% while the same exchange rate increase during a month at the 95th percentile of IQR will lead prices to rise by 2.6%.

Since our MRPT specification conditions on price adjustment and Gopinath and Itskhoki (2010) show an important relationship between frequency and long-run passthrough, it is natural to ask whether IQR effects are driven by changes in frequency. Column (3) provides evidence that this is not the case. This regression adds controls for $freq_t$ and $freq_t \times \Delta e$ and shows that IQR effects are unchanged.[25] While frequency is perhaps the most obvious potential confounding effect, many other variables also move across time. In column (4), we allow passthrough to vary with a wide array of additional controls. In particular, we introduces interactions of Δe with the frequency of product substitution, the time-series volatility of the exchange rate, seasonality, secular time trends and the business cycle, as measured by GDP growth.[26]

Product substitution can potentially affect measured passthrough as shown in Nakamura and Steinsson (2012), and changes in the volatility of exchange rates might affect both dispersion and passthrough. We allow for secular trends since a prior debate using aggregate data has sometimes found such trends, the presence of which could lead to spurious relationships with dispersion.[27] Finally, since Figure 1 shows

[25] Controlling for frequency also partially proxies for changes in the importance of price-spell censoring, which can in turn potentially affect measures of both passthrough and dispersion through selection effects as described in Section 3.2.

[26] The time-series volatility of the exchange rate is measured as the standard-deviation of the bilateral exchange rate associated with a particular item's country of origin in the 12-month period around the month of its price change. Seasonality is captured with 12 month dummies, interacted with exchange rate changes. Secular changes are modeled as a linear trend in passthrough. Real GDP growth is chained GDP growth in the quarter corresponding to a given month's price change.

[27] For example, Marazzi et al. (2005) argues that aggregate measures of passthrough have declined, but Hellerstein et al. (2006) show this is largely driven by commodities. Using our micro data, we find no evidence of trends in MRPT regardless of the treatment of commodities. This difference between our micro results and Marazzi et al. (2005) arises in part because their study uses aggregate data which means that their passthrough statistic measures $frequency \times$ MRPT rather than just

that IQR is countercyclical, we control for GDP growth to show that our dispersion-passthrough relationship is not entirely a business cycle-passthrough relationship. In Appendix A.1, we show results are similar with a variety of other business cycle controls.

Introducing all of these controls mildly reduces the one SD effect of IQR on passthrough from 0.07 to 0.05 but our effect of interest remains economically large and highly statistically significant.[28] Thus, the positive relationship between dispersion and passthrough is robust to including a large set of time-varying covariates. The final columns of Table 1 show that our results also hold when using the standard deviation as an alternative measure of dispersion instead of the IQR. In Appendix A.1, we repeat results separately for imports from individual countries as well as for different product classifications to show that changing composition of the sample along these dimensions does not drive our results.

2.4 Robustness

2.4.1 Does the Great Recession Drive All Results?

Since the increase in IQR during the Great Recession shown in Figure 1 is a large outlier, it is important to show that our results are not driven by this single period. In Table 2, we repeat our regressions excluding the Great Recession.[29] We continue to find large and significant effects of dispersion on passthrough even outside the Great Recession. While coefficients are somewhat smaller, it is important to note that units are standardized so that the regression coefficients represent one-standard deviation effects. Most of the decline in the coefficient on $IQR \times \Delta e$ reflects the fact that IQR has a lower standard deviation outside of the Great Recession rather than a decline in the response of passthrough to a given change in IQR: computing the elasticity of passthrough to IQR, instead of one standard deviation effects, delivers an elasticity of 2.57 over the entire sample and 2.23 when excluding the Great Recession. These large and similar elasticities are not surprising in light of the scatter plot in Figure 2.

We now show that the time-series relationship between dispersion and passthrough also holds within sectors. This provides additional evidence that results are not driven solely by the Great Recession or any other confounding aggregate shock since each sector exhibits different IQR time-series. In Column (1) of Table 3, we repeat Regression (2), but replace IQR with IQR_{sector}, which is the interquartile range of all price changes in an item's broad sector in a given month.[30] The effect of IQR_{sector} is large and significant. However, it is possible that this is driven by movements in IQR_{sector} that are common across sectors. That is, if IQR_{sector} increases for all sectors then so does IQR, which means the positive coefficient in Column (1) could potentially just be picking up the previously documented IQR effects. Column (2) shows that this is not the case since IQR and IQR_{sector} both independently increase passthrough. However, this could still be driven by the response to a confounding shock which increases passthrough, IQR and IQR_{sector}. To eliminate effects of common shocks which moves both series, Columns (3) and (4) only include changes in IQR_{sector} relative to changes in IQR. Column (3)

MRPT, and frequency did have a declining trend over the period they studied.

[28] It is unsurprising that introducing a large set of covariates which have previously been shown to have importance for passthrough would absorb some of the initial effects of IQR. Nevertheless, this attenuation is small, and we actually cannot reject equality of coefficients at conventional significance levels.

[29] We exclude all price changes which occur during the Great Recession, but some price changes which occur shortly after the Great Recession might be changing from a price previously determined during the Great Recession. Repeating results using only completed price spells which are entirely outside of the Great Recession delivers nearly identical results.

[30] That is the 23 Sections of the HS Code, some examples include: prepared foodstuffs, mineral products, textiles.

measures relative changes using the absolute deviation of IQR_{sector} from IQR while Column (4) uses the percentage deviation. These specifications show that sectors with relative increases in dispersion have relative increases in passthrough. Finally, in Column (5), we redo the regression in Column (1) but with the addition of month-date dummies and month-date dummies interacted with Δe. This is the most stringent test of sector specific effects since month dummies absorb the effects of *any* common aggregate shocks which affect passthrough, not just shocks which change aggregate IQR. For example, if the Great Recession increases overall passthrough and IQR through any mechanism, this will be absorbed by these dummies and will not generate a positive coefficient on $IQR_{sector} \times \Delta e$, since that coefficient is only identified off of differences across sectors *within* a given calendar month.

Across all specifications, there is an economically and statistically significant positive relationship between dispersion within sectors and passthrough. Together this greatly alleviates any concerns that our results are spurious or explained by failure to control for confounding shocks.[31]

2.4.2 Misspecification

Our baseline regression 2 is intentionally simple, to illustrate effects transparently and align our results with the existing micro oriented passthrough literature. In particular, we impose a linear relationship between passthrough and IQR and assume only exchange rate movements accumulated over the current spell affect current price changes. The presence of large shocks to exchange rates or IQR could make the first assumption problematic while strategic complementarities or other forces which lead firms to adjust prices gradually could violate the second. More generally, we address misspecification concerns in two ways. 1) In this section, we show that our empirical results are robust to many alternative specifications which are less sensitive to such concerns. 2) In our quantitative model, we use an indirect inference procedure which maps true structural relationships into the same reduced form regression used in our empirical analysis to show that misspecification within that structural model cannot explain our results.

Table 4 Column (1) includes $(\Delta e)^2$ and $(IQR)^2$ terms to show that the relationship between IQR and passthrough is not spuriously driven by non-linearities in the true passthrough specification. Column (2) shows that non-linear effects of IQR on passthrough are insignificant. Column (3) allows for IQR effects on passthrough to depend non-linearly on Δe. Unsurprisingly, passthrough rises with the size of exchange rate shocks, but we find similar interactions with dispersion. Columns (4) and (5) include cumulative exchange rate movements over prior price spells rather than just over the current spell. Consistent with our theoretical model in 4, increasing IQR increases the response of prices to both current and lagged exchange rate movements. In Columns (6) and (7) we split our sample separately into observations with positive and negative exchange rate movements to allow for asymmetry in the response of prices to shocks of opposite signs. We find strong positive relationships in both sub-samples. Column (8) shows results are similar when only including items with 5+ price changes. Using items with many price changes reduces concerns that results might be driven by censoring or biases induced by conditioning on price adjustment. Column (9) instead restricts to items with few price changes and again shows a positive relationship. In Appendix Table A4 we also show results are similar for passthrough specifications which do not condition on price adjustment and so are unaffected by censoring. As we discuss in Section 3.2, such specifications

[31]The estimates in Column (2) suggest that roughly 2/3 of the passthrough-dispersion relationship is driven by factors common to all sectors while 1/3 is driven by sector specific factors. Since columns (3)-(6) remove these common effects it is not surprising that they deliver passthrough-dispersion relationships which are somewhat dampened relative to Table 1.

are less useful for identification but can still be helpful for diagnosing misspecification. Finally, column (10) runs a median instead of OLS regression to limit outlier influence.

2.4.3 Cross-Item Evidence

In our final set of robustness results, we show that our results extend from the time-series to the cross-section. In particular, we calculate "item-level" dispersion: the standard deviation of all non-zero price changes for a particular item across time and show that item-level dispersion is positively correlated with that item's exchange rate passthrough. This robustness check is useful in two ways: 1) Gopinath and Itskhoki (2010) argue that heterogeneity in responsiveness across items is crucial for understanding long-run frequency-passthrough differences in the cross-section. Under this hypothesis, we should also see a positive dispersion-passthrough relationship across items in the data. 2) More importantly, if items differ in their dispersion and passthrough, then we want to ensure that the time-series relationship between dispersion and passthrough is not driven by changing sample composition across time.

Table A5 shows that there is indeed a positive relationship between the standard deviation of item level price changes and passthrough. Furthermore, this relationship is not driven by differences in the frequency of adjustment across items, and both month-level dispersion (IQR) and item-level dispersion (XSD) have independent positive effects on passthrough. This means that time-series results are not explained by composition shifts from low dispersion and passthrough items to high dispersion and passthrough items across time. Appendix A.1 shows robustness of these cross-item results to many issues raised above.

3 Basic theoretical framework

3.1 Flexible price model

In this section we lay out a simple partial equilibrium framework with flexible prices that builds on Burstein and Gopinath (2013) to show how economic primitives shape the relationship between exchange rate passthrough and price change dispersion. We begin with this special case since it allows us to provide most of the intuition for our identification strategy with simple analytical formulas. We show that in this special case, time-variation in responsiveness is a necessary condition to deliver a positive relationship between dispersion and passthrough. However, this special case requires strong assumptions and eliminates some potentially important forces that shape the passthrough-dispersion relationship. Thus, in the following section, we relax many of these assumptions using a more empirically realistic model and show that this only strengthens the conclusions from the simple framework.

Consider the partial equilibrium decision problem of a foreign exporter selling goods priced flexibly in dollars in the U.S. The firm faces a common exchange rate, e_t, and an idiosyncratic cost shock, η_{it}, and each process follows an independent random walk.[32] The optimal flexible price (in logs) of item i at the border is the sum of the gross markup (μ_{it}) and dollar marginal cost ($mc_{it}(e_t, \eta_{it})$) which depends on both the exchange rate and the idiosyncratic shock.

$$p_{it} = \mu_{it} + mc_{it}(e_t, \eta_{it}). \tag{3}$$

[32] This independence is without loss of generality since any correlated component can be subsumed in (unobserved) α_t.

Taking the total derivative of equation (3) and rearranging gives an expression for a firm's optimal price change in terms of objects which the firm treats as exogenous[33]:

$$\Delta p_{i,t} = \frac{\alpha_t}{1+\Gamma_t}\Delta e_t + \frac{1}{1+\Gamma_t}\epsilon_{i,t} \tag{4}$$

where $\Gamma_t \equiv -\frac{\partial \mu_{it}}{\partial(\Delta p_{it}-\Delta p_t)}$ is the elasticity of a firm's optimal markup with respect to its relative price, $\alpha_t \equiv \frac{\partial mc_{it}}{\partial e_t}$ is the elasticity of the dollar marginal cost to the exchange rate, and $\epsilon_{it} = \Delta\eta_{it}$ is the innovation in the idiosyncratic cost shock with $\epsilon_{i,t} \sim G(0, \sigma_{\epsilon t}^2)$. For reasons described below, we refer to Γ_t as "responsiveness", α_t as "import intensity" and $\sigma_{\epsilon t}$ as "volatility". To make the setup as simple as possible, we do not model the underlying primitives that give rise to variation in these parameters, and we assume they vary across time independently from each other but are common across all firms.[34]

Under these assumptions, taking the expected value of equation (4) across all firms i gives an expression for period t exchange rate passthrough[35]:

$$\beta_t^{Flex} \equiv E^i \frac{\Delta p_{i,t}}{\Delta e_t} = \frac{\alpha_t}{1+\Gamma_t} \tag{5}$$

This formula shows that exchange rate passthrough is increasing in the import intensity of marginal cost, α_t. If marginal cost is entirely denominated in dollars ($\alpha_t = 0$), then exchange rate shocks are irrelevant for the optimal dollar price and passthrough is zero. The formula also shows that passthrough declines as the sensitivity of optimal markups to relative prices, Γ_t, rises.[36] If $\Gamma_t = 0$, as in models with constant markups like those with CES demand, a firm's optimal markup does not change as its price deviates from its competitors and passthrough is maximized. If $\Gamma_t > 0$, then as the price of the firm increases relative to its competitors its optimal markup declines. This means that increases in Γ_t reduce firms' optimal price responses to cost shocks.

Since lowering Γ_t makes firms more responsive to all cost shocks, we refer to lowering Γ_t as increasing total "responsiveness". If responsiveness is high (low Γ_t), firms will respond more strongly to both idiosyncratic and exchange rate shocks. In contrast, equation (4) shows that α_t affects how much firms respond to exchange rate shocks but not to idiosyncratic shocks. Thus, we use the term responsiveness exclusively to refer to Γ_t, which determines general cost passthrough of all shocks.

Notice that in this flexible price framework, passthrough is determined exclusively by these two factors. Importantly, this means that changing volatility, $\sigma_{\epsilon t}$, has no effect on passthrough when prices are fully flexible. This is because passthrough is scale invariant: doubling the size of a cost shock doubles the optimal price response leaving passthrough, which is measured in percentage terms, unchanged.

We can also use equation (4) to show how α_t, Γ_t and $\sigma_{\epsilon t}$ affect the cross-sectional standard deviation

[33]This derivation assumes constant sectoral price index p_t. Appendix B.3 extends results to GE.

[34]In our fully fledged quantitative model, both Γ and α are derived from firm behavior but both nevertheless move one-for-one with exogenous parameters.

[35]Superscripts in expectation and variance formulas refer to whether results are averaging over firms (i) or time (t)

[36]Γ captures classic pricing to market channels of Dornbusch (1987) and Krugman (1987), where firms adjust optimal markups in response to cost shocks, leading to incomplete passthrough. The open economy literature has studied mechanisms which can generate $\Gamma > 0$, but we require time-variation in this parameter. Appendix B shows this is predicted by the growing set of models in which countercyclical dispersion arises as an endogenous phenomenon, so that there is a heretofore unrecognized link between models explaining passthrough and those explaining time-varying dispersion.

of price changes at a moment in time t (month-level dispersion):

$$Std^i\left(\Delta p_{i,t}\right)=\sqrt{Var^i\left(\frac{\alpha_t\Delta e_t}{1+\Gamma_t}\right)+Var^i\left(\frac{\epsilon_{it}}{1+\Gamma_t}\right)+2Cov^i\left(\frac{\alpha_t\Delta e_t}{1+\Gamma_t},\frac{\epsilon_{it}}{1+\Gamma_t}\right)}=\left(\frac{1}{1+\Gamma_t}\right)\sigma_{\epsilon t}. \quad (6)$$

In this expression the first term is equal to zero because it only includes objects that are common across firms while the third term is equal to zero because exchange rate and idiosyncratic cost innovations are assumed independent (WLOG). Equation 6 shows that month-level dispersion increases with idiosyncratic volatility and with responsiveness. The variance of exchange rate shocks does not affect dispersion in this simple model because exchange shocks and the level of import intensity are common across firms.[37]

Comparing equations (5) and (6), it is clear the only parameter that can that generate variation consistent with our empirical results (Figure 2) – a positive time-series correlation between passthrough and dispersion – is variation in responsiveness. This is shown formally in the following proposition:

Proposition 1 *Assume that α_t, Γ_t and $\sigma_{\epsilon t}$ are independent time-series processes. Then the time-series correlation coefficient between exchange rate passthrough, $E^i\frac{\Delta p_{i,t}}{\Delta e_t}$, and the cross-sectional standard deviation of price changes, $Std^i\left(\Delta p_{i,t}\right)$, is given by the following expression:*

$$Corr^t\left(E^i\frac{\Delta p_{i,t}}{\Delta e_t},Std^i\left(\Delta p_{i,t}\right)\right)=\frac{E^t\left[\alpha_t\right]E^t\left[\sigma_{\epsilon t}\right]Var^t\left(\frac{1}{1+\Gamma_t}\right)}{Std^t\left(\frac{\alpha_t}{1+\Gamma_t}\right)Std^t\left(\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right)}$$

Proof. See Appendix B.2 ■

As long as passthrough and dispersion are both positive $\left(E^t\left[\alpha_t\right]>0;E^t\left[\sigma_{\epsilon t}\right]>0\right)$, then time-variation in responsiveness is a necessary condition for generating a positive relationship between passthrough and dispersion. In a flexible price model, variation in the other parameters affects the magnitude of this correlation but not its sign. While this does not rule out the presence of other shocks, it indicates that responsiveness is crucial for generating empirically observed positive relationships.

3.2 Price Stickiness

We now show this logic extends to the realistic case when there is price stickiness. This extension is important for three reasons. 1) Price stickiness is a pervasive feature of micro price data: the median price duration for imports to the U.S. is around 11 months. 2) Allowing for stickiness creates a channel through which volatility shocks affect measured passthrough. In particular, in menu cost models where price adjustment is endogenous, conditioning on price adjustment induces a selection bias which affects MRPT estimates.[38] 3) It shows that in the presence of realistic price stickiness, identification requires using a measure of passthrough which conditions on price adjustment.

To understand how primitives of a menu cost model affect measured passthrough, it is useful to

[37] This is no longer true once we allow for price stickiness as in the next sub-section. Then increases in α_t and $Var^t(\Delta e_t)$ will increase price dispersion. However, we show this effect is quantitatively small.

[38] This is a selection bias in the classic statistical sense, in which residuals (ε) are uncorrelated with the explanatory variable (Δe) in the population but are correlated in the sample selected for our regression. We are not first to notice this bias. See the brief discussion in footnotes 7 and 26 of Gopinath et al. (2010). Note that in Calvo pricing models where price adjustment is exogenous, this bias is absent but in this case volatility increases still do not increase passthrough.

examine our baseline MRPT specification in equation (1) with regression coefficient equal to:

$$\widehat{\beta}_t = \frac{Cov^i(\Delta p_{i,t}, \Delta e_t)}{Var^i(\Delta e_t)} = \beta_t^{flex} + \underbrace{Cov^i(\epsilon_{i,t}, \Delta e_t)/Var^i(\Delta e_t)}_{\text{selection bias}},$$

where β_t^{Flex} is the unconditional response of desired prices to exchange rate movements, and, as is in our empirical results, Δe_t is the cumulative exchange rate change since the firm last adjusted.[39] Menu cost models induce $Cov^{it}(\epsilon_{i,t}, \Delta e_t) > 0$ for firms that choose to adjust, even though the unconditional covariance between these two shocks is zero. This is because in a menu cost model a firm is more likely to adjust when idiosyncratic and exchange rate shocks reinforce each other. This implies that estimated passthrough conditional on price adjustment, $\widehat{\beta}_t$, is larger than unconditional desired passthrough, β_t^{Flex}.

Higher menu costs lead firms to adjust less often and by larger amounts (which increases the dispersion of price changes) as firms economize on the number of times they adjust prices. Increases in the menu cost lead to a wider range of inaction, which leads the importance of selection effects and $Cov^i(\epsilon_{i,t}, \Delta e_t)$ to increase. This then leads to an increase in measured MRPT.

Conversely, greater volatility lowers MRPT because the magnitude of the selection bias is decreasing in the size of idiosyncratic shocks: as the size of idiosyncratic shocks increases, firms are more likely to adjust their prices for purely idiosyncratic reasons, which lowers $Cov^i(\epsilon_{i,t}, \Delta e_t)$, conditional on adjustment. At the same time, larger shocks mean greater price dispersion. Thus changes in the volatility of idiosyncratic shocks induce a counterfactual *negative* relationship between passthrough and dispersion.

As a final observation on the role of price stickiness for our analysis, we now show that the presence of stickiness makes conditioning on price adjusting crucial for our identification argument. To see this, note that unconditional passthrough is equal to passthrough conditional on adjustment times the frequency of adjustment: $\widehat{\beta}_t \times freq_t$. While increases in idiosyncratic volatility lead $\widehat{\beta}_t$ to decrease, they also increase $freq_t$. If the frequency effect dominates (which it strongly does in our quantitative model) then volatility shocks induce a positive correlation between unconditional passthrough and dispersion. Responsiveness shocks also induce a positive relationship between these statistics so that volatility and responsiveness cannot be separately identified using unconditional passthrough.[40]

Reviewing the conclusions from Section 3, it follows that changes in volatility, $\sigma_{\epsilon t}$ should generate a counterfactual negative relationship between measured MRPT and price change dispersion while changes in Γ_t or in menu costs should generate a positive relationship. However, we now show that only the responsiveness channel arising from variation in Γ_t is quantitatively successful.

4 Quantitative Model

We now formally assess the theoretical link between price change dispersion and exchange rate passthrough in an estimable quantitative model. The model allows for the theoretical channels just discussed but also includes indirect equilibrium effects that the simple model in Section 3.1 ignored. In Appendix B we show that a variety of models which generate time-variation in dispersion endogenously ultimately do so by generating variation in Γ. Since these models all have a similar reduced form interpretation, our

[39] $Var^i(\Delta e_t) > 0$ even though the exchange is common across firms because of staggered price adjustment.

[40] While we could potentially get identification from the magnitude rather than signs of correlations, this would rely on stronger structural modeling decisions. Conditional passthrough yields more direct and robust identification.

qualitative insights do not require taking a stand on a particular source of Γ variation. However, moving to quantitative results requires specifying a particular mechanism and functional form for this variation. We do so building on the menu cost model of Gopinath and Itskhoki (2010) which delivers cross-sectional heterogeneity in responsiveness through a Kimball demand function with heterogenous "super-elasticity" of demand in preferences. We intentionally build on this workhorse model of incomplete passthrough for two main reasons: 1) Gopinath and Itskhoki (2010) show that this model can hit a variety of cross-sectional microeconomic facts, and it is important that matching our new facts not come at the expense of missing old ones. 2) It is highly parsimonious relative to many other models which give rise to variation in responsiveness. Importantly, this allows us to include a variety of aggregate shocks when estimating the model to match our earlier time-series evidence. However, it is important to again emphasize that this does not imply that we think other mechanisms such as experimentation or incomplete information are unimportant, and in reality many of these mechanisms are likely simultaneously present in the data.

4.1 Model Description and Calibration

We begin by describing the model with no aggregate shocks, the baseline calibration and show simple comparative statics to provide a quantitative complement to the results in Section 3. We then introduce aggregate shocks to these parameters. In order to infer the importance of various shocks we estimate the model via indirect inference: for a given set of shocks, we solve for the sectoral equilibrium of the model and simulate data mimicking BLS procedures, run our empirical regressions on this simulated data and compare these results to those in Section 2.3. We then repeat this process repeatedly with alternative sets of aggregate shocks until we find the best fit to the empirical data.

4.1.1 Industry Demand Aggregator

The industry is characterized by a continuum of varieties indexed by j. There is a unit measure of domestic varieties and a measure $\omega < 1$ of foreign varieties available for domestic consumption, which captures the idea that not all varieties are traded internationally.

We generate variable markups by utilizing a Kimball (1995) style aggregator:

$$\frac{1}{|\Omega|}\int_{\Omega}\Psi\left(\frac{|\Omega|\,C_j}{C}\right)dj = 1 \tag{7}$$

with $\Psi(1) = 1, \Psi'(.) > 0$ and $\Psi''(.) < 0$. C_j is the quantity demanded of variety $j \in \Omega$, where Ω is the set of all varieties available domestically. Ω has measure $1 + \omega$. Individual varieties are aggregated into a final consumption good C. This intermediate aggregator contains the CES specification as a special case. The demand function for C_j implied by equation (7) is:

$$C_j = \varphi\left(D\frac{P_j}{P}\right)\frac{C}{|\Omega|}, \text{ where } \varphi(.) \equiv \Psi'^{-1}(.) \tag{8}$$

Here P_j is the price of variety j, P is the sectoral price index and $D \equiv \left[\int_{\Omega}\Psi'\left(\frac{|\Omega|C_j}{C}\right)\frac{C_j}{C}dj\right]$. P is defined implicitly by the following equation

$$PC = \int_{\Omega}P_jC_jdj$$

4.1.2 Firm's problem

Consider the problem of a firm producing variety j. Foreign and domestic firms face symmetric problems and we label foreign variables with asterisks. The firm faces a constant exogenous marginal cost:

$$MC_{jt} = \frac{W_t^{1-\alpha}(W_t^*)^\alpha}{A_{jt}}$$

where W_t is the domestic wage and the parameter α is the share of foreign inputs in the firm's cost function. A_{jt} denotes idiosyncratic productivity, which follows an AR(1) in logs:

$$\log(A_{jt}) = \rho_A \log(A_{j,t-1}) + \mu_{jt} \ \text{ with } \ \mu_{jt} \ \sim \ iid \ N(0, \sigma_A)$$

Combining unit revenues, costs and demand yields the firm's profits from variety j in the domestic market:

$$\Pi_{jt} = \left[P_{jt} - \frac{W_t^{1-\alpha}(W_t^*)^\alpha}{A_{jt}}\right] C_{jt}$$

Firms are price-setters but face a menu cost κ when adjusting prices. Let the state vector of firm j be $S_{jt} = (P_{j,t-1}, A_{jt}; P_t, W_t, W_t^*)$ where $P_{j,t-1}$ and A_{jt} are idiosyncratic states and P_t, W_t, and W_t^* are aggregate states. The value of a firm selling variety j is characterized by the following Bellman equation:

$$\begin{aligned}
V^N(S_{jt}) &= \Pi_{jt}(S_{jt}) + E\{Q(S_{jt+1})V(S_{jt+1})\} \\
V^A(S_{jt}) &= \max_{P_{jt}} \{\Pi_{jt}(S_{jt}) + E\{Q(S_{jt+1})V(S_{jt+1})\}\} \\
V(S_{jt}) &= \max\{V^N(S_{jt}), V^A(S_{jt}) - \kappa\}
\end{aligned}$$

where $V^N(.)$ is the value function if the firm does not adjust its price, $V^A(.)$ is the value function if it adjusts, and $V(.)$ is the value of making the optimal price adjustment decision. $Q(S_{jt+1})$ is the stochastic discount factor. Each period the firm chooses whether to adjust its price by comparing the value of not adjusting to the value of adjusting net of the menu cost.

4.1.3 Sectoral equilibrium

We define $e_t \equiv \ln(W_t^*/W_t)$ as the log real exchange rate. Sectoral equilibrium is characterized by a path of the sectoral price level, $\{P_t\}$, consistent with optimal pricing policies of firms given the exogenous idiosyncratic productivity process and exchange rate. This sectoral equilibrium allows for indirect effects that we shut down in Section 3.1. Following Krusell and Smith (1998) and its open economy implementation in Gopinath and Itskhoki (2010), we assume that $E_t \ln P_{t+1} = \gamma_0 + \gamma_1 \ln P_t + \gamma_2 e_t$. We then solve the firm's Bellman equation given a conjecture for γ, simulate the model and iterate to convergence. As in Gopinath and Itskhoki (2010), this forecasting rule is highly accurate in equilibrium.

Since our empirical analysis is restricted to dollar prices we assume all prices are set in the domestic currency. Following Gopinath and Itskhoki (2010), we assume that $W_t = 1$ so that all fluctuations in the real exchange rate arise from fluctuations in W_t^*. In economic terms, this amounts to an assumption that the value of the domestic currency and real wage are stable relative to the exchange rate. It is indeed the case in the U.S. that exchange rates have little explanatory power for these variables since net exports are a small part of the overall economy.

4.1.4 Calibration

While there are a number of strategic complementarities that can generate variable markups (and thus incomplete passthrough), the specific form we explore in our quantitative results is the Klenow and Willis (2006) specification of the Kimball aggregator (equation 7):

$$\Psi = \left[1 - \varepsilon \ln\left(\frac{\sigma x_j}{\sigma - 1}\right)\right]^{\frac{\sigma}{\varepsilon}}, \quad \text{where} \quad x_j \equiv D\frac{P_j}{P}$$

This demand specification is governed by two parameters: $\sigma > 1$ and $\varepsilon > 0$. The elasticity and the super-elasticity of demand are given by:

$$\widetilde{\sigma}(x_j) = \frac{\sigma}{1 - \varepsilon \ln\left(\frac{\sigma x_j}{\sigma - 1}\right)} \quad \text{and} \quad \widetilde{\varepsilon}(x_j) = \frac{\varepsilon}{1 - \varepsilon \ln\left(\frac{\sigma x_j}{\sigma - 1}\right)}$$

.Under these assumptions the flexible price markup is given by

$$\widetilde{\mu} = \frac{\sigma}{\sigma - 1 + \varepsilon \ln\left(\frac{\sigma x_j}{\sigma - 1}\right)}$$

so that when $\varepsilon \longrightarrow 0$, we get a CES demand structure with an elasticity of substitution equal to σ and a markup equal to $\frac{\sigma}{\sigma-1}$. The price elasticity of desired markups is given by:

$$\Gamma \equiv -\frac{\partial \ln \widetilde{\mu}}{\partial \ln P_j} = \frac{\varepsilon}{\sigma - 1 + \varepsilon \ln\left(\frac{\sigma x_j}{\sigma - 1}\right)}.$$

Thus, responsiveness is decreasing in ε and increasing in σ (if $\varepsilon > 0$). Since we do not directly observe σ or ε we cannot separately identify changes in these parameters. For simplicity and following Gopinath and Itskhoki (2010), we assume that variation in Γ is driven solely by ε but note that variation in σ would yield similar results. We return to this point in Appendix B which explores sources of Γ variation.

Table 5 shows calibrated values for all parameters. The period in our model is one month and we calibrate the discount rate to generate a 4% annual real interest rate ($\beta = 0.96^{1/12}$). We set the elasticity of demand, σ, equal to 5 to yield a steady-state markup of 25%. This is the middle of the range estimated for U.S. imports by Broda and Weinstein (2006). Since empirically the exchange rate is very persistent, we assume for computational simplicity that the log exchange rate, e, follows a random walk. We set the mean increment of the real exchange rate innovation to 2.5% following Gopinath and Itskhoki (2010). To calibrate the share of imports, $\frac{\omega}{1+\omega}$, we use the share of imports as a percentage of GDP from the Bureau of Economic Analysis.[41] The average of this import share for the U.S. over our sample period is 14.5%, which implies that $\omega = 0.17$.We set the persistence of the idiosyncratic shock process, ρ_A, equal to 0.85, which is in between the values used by Gopinath and Itskhoki (2010) and Nakamura and Steinsson (2008), and we set $\kappa = 0.05$ to match the frequency of price adjustment of 17% in our sample.[42]

[41]This import share is important to allow for realistic sectoral equilibrium effects, as discussed in Appendix B.

[42]Note that our sample in both the model and data only includes items with at least two price changes, so this frequency is moderately higher than the frequency of price adjust of all items in the IPP.

Finally, the parameters α, ε, and σ_A are jointly calibrated to match three moments of the data: average passthrough, the R^2 from our MRPT regression and the mean standard deviation of item level price changes. In Appendix Figure B.4 we plot the relationship between each parameter and these moments, but to get a sense for why these moments separately identify our parameters, it is useful to remember the intuition from our simple model and our baseline MRPT regression:

$$\Delta p_{i,t} = \beta \Delta e_t + \epsilon_{i,t} \tag{9}$$

Decreasing ε means that firms respond more to both exchange rate movements and idiosyncratic shocks when adjusting prices. This increases passthrough and the standard deviation of price changes but has little effect on the R^2 from estimating equation (9) since lowering ε increases both explained variance coming from Δe_t and unexplained variance coming from $\epsilon_{i,t}$ by roughly equal amounts. Increasing σ_A leads to a large increase in the variance of price changes and a decrease in estimated passthrough since the selection bias conditional on price adjustment is decreasing in σ_A. Increasing σ_A also leads to a large decrease in R^2, since amplifying $\epsilon_{i,t}$ increases the residual sum of squares. Finally, increasing α leads to large increases in measured passthrough but has little effect on the variance of price changes since the variance of price changes is almost entirely driven by idiosyncratic shocks. At the same time, increasing α leads to modest increase in R^2 since it increases the signal to noise ratio in the passthrough regression.

Thus, movements in these three parameters produce distinctly different effects on the average level of passthrough, the R^2 from our MRPT regression, and the mean standard deviation of item level price changes so that these three moments allow us to identify our parameters of interest. We find that the best fit parameters for α, ε, and σ_A are 0.165, 2.35 and 0.08, respectively.

4.2 Simple Comparative Statics

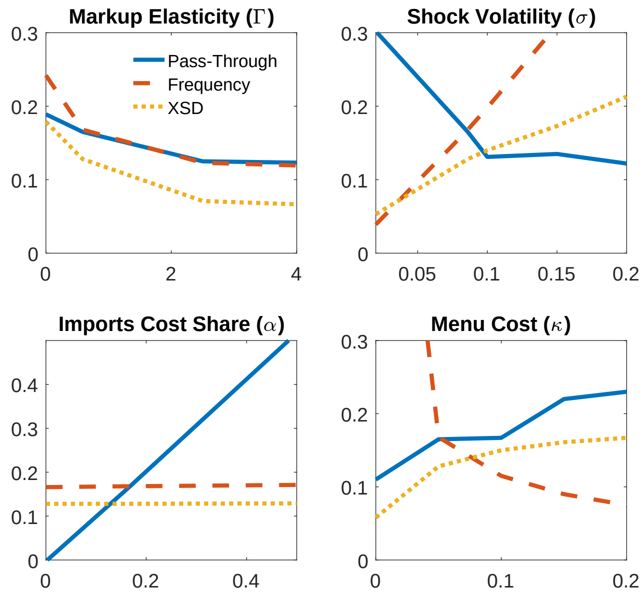
To understand the role of various channels in explaining the empirical relationship between MRPT and the dispersion of price changes, we begin with a simple comparative statics exercise. Each panel of Figure 4 shows results when we fix three of ε, κ, α and σ_A at their baseline calibrated values and vary the fourth parameter. For each value of this parameter we solve the model, simulate a panel of firms with the same number of observations as in the BLS data and compute MRPT, frequency and the standard deviation of price changes exactly as in Section 2.

This comparative statics exercise allows us to trace out how changes in structural parameters affect the joint-behavior of these 3 statistics and provides a quantitative counterpart to the intuition in Section 3.1.[43] This cannot be mapped directly to the empirical results in Section 2.3, since it is showing the implications of permanently changing parameters within a model and so does not correspond exactly to our empirical exercise. However, it gives a sense of the quantitative response of observable moments to underlying structural parameters and so is useful for guiding the indirect inference exercise which follows. There we introduce aggregate shocks, simulate time-series and run regressions just as in Section 2.3.

The top-left panel shows the effects of changing responsiveness by varying the markup elasticity Γ from

[43] The relation between our comparative statics and those in Gopinath and Itskhoki (2010) Proposition 3 bears some mention. They find that in a simple static model, passthrough increases with α, declines with ε and is unaffected by κ or σ_A. Our conclusion for α and ε is identical, but our results for κ and σ_A differ because we study MRPT while they study LRPT. LRPT is not subject to the selection effects that induce $cov(\epsilon_{i,t}, \Delta e_t) > 0$ but these effects are important for MRPT.

Figure 4: Comparative Statics



Holding all other parameters at their baseline values, this figures shows the effect of varying individual parameters on frequency, passthrough and the standard deviation of price changes. The solid blue line shows MRPT, the dashed red line shows frequency and the dotted yellow line shows the standard deviation of price changes. The x-axis in each plot shows the value of the parameter being varied.

0 to 4 (corresponding to moving ε from 0 to 16). It is apparent that lowering responsiveness (increasing Γ) causes passthrough, frequency and the standard deviation of price changes to all fall. The upper-right panel shows that increasing the volatility of shocks σ_A also increases the standard deviation of price changes and frequency but instead lowers passthrough. This is because increasing σ_A makes firms more likely to adjust their prices for purely idiosyncratic reasons, which reduces selection effects and MRPT. Thus, variation in responsiveness results in a positive passthrough-dispersion relationship while variation in volatility generates a counterfactual negative relationship.

The bottom-left panel shows what happens as we vary α from 0 to 0.5. This leads to large changes in MRPT but negligible movements in the variance of price changes and frequency. This is because idiosyncratic shocks are much more important than exchange rate shocks for explaining price change dispersion so that increasing the sensitivity to the exchange rate barely raises price change dispersion.

The bottom-right panel shows model results when we vary κ from 0 to 0.2. Consistent with the discussion in the previous section, variation in κ generates a positive relationship between MRPT and dispersion. This positive correlation occurs because higher menu costs lead firms to tolerate wider price imbalances before adjusting, which amplifies selection effects. This increases price change dispersion as well as measured passthrough, but it also leads to a large decline in the frequency of price adjustment. Since this strong negative relationship between dispersion and frequency is counterfactual, this is what ultimately leads us to reject variation in menu costs as an explanation for our empirical results.

While we view this comparative statics exercise as very informative, it has some weaknesses: 1) In the data, we are sorting months and firms into bins by the dispersion of price changes. Our comparative statics exercise instead computes results for a series of models that vary by a single parameter, so we are implicitly sorting by this (unobserved) parameter rather than by price change dispersion so there is not a clean match between our comparative statics simulations and our empirical exercise. 2) In the data, firms and time periods likely differ along many dimensions simultaneously so that heterogeneity is unlikely to be well-captured by a single parameter. 3) The comparative statics exercise is relatively informal. For example, both κ and ε generate positive relationships between MRPT and dispersion and there is little formal guidance for which is a better fit even along this single moment. We thus turn to a formal estimation strategy that squarely addresses each of these weaknesses.

4.3 Indirect Inference

In this section, we allow for aggregate shocks, which we assume are unobserved by the econometrician. We then formally estimate the importance of different shocks in explaining our empirical results using indirect inference. More specifically, we assume that

$$\begin{aligned}
\ln \varepsilon_t &= \ln \varepsilon^{ss}(1-\rho) + \rho \ln \varepsilon_{t-1} + \epsilon_t \text{ with } \epsilon_t \sim N(0, \sigma_\varepsilon) \\
\ln \sigma_t &= \ln \sigma^{ss}(1-\rho) + \rho \ln \sigma_{t-1} + s_t \text{ with } s_t \sim N(0, \sigma_\sigma) \\
\ln \kappa_t &= \ln \kappa^{ss}(1-\rho) + \rho \ln \kappa_{t-1} + \gamma_t \text{ with } \gamma_t \sim N(0, \sigma_\kappa).
\end{aligned}$$

where $\varepsilon^{ss}, \sigma^{ss}, \kappa^{ss}$ are the steady-state values shown in Table 5. Since each additional aggregate shock increases the computational burden in estimation substantially, and since Figure 4 shows that changes in α do not affect dispersion, we do not model shocks to α.[44] Once we introduce aggregate shocks, we must also modify the equilibrium transition rules, which assume then take the form:

$$\begin{aligned}
E_t \ln P_{t+1} = {} & \gamma_0 + \gamma_1 \ln P_t + \gamma_2 e_t + \gamma_3 \ln \varepsilon_t + \gamma_4 \ln P_t \ln \varepsilon_t + \gamma_5 e_t \ln \varepsilon_t \\
& + \gamma_6 \ln \sigma_t + \gamma_7 \ln P_t \ln \sigma_t + \gamma_7 e_t \ln \sigma_t + \gamma_8 \ln \kappa_t + \gamma_9 \ln P_t \ln \kappa_t + \gamma_{10} e_t \ln \kappa_t.
\end{aligned}$$

That is, we allow the price level to have an intercept, persistence and sensitivity to exchange rates that depends on the current realization of our three aggregate shocks. For a given set of parameters, we solve for the model equilibrium and then construct a firm panel, which we sample exactly as in BLS microdata to account for small sample issues or other misspecification concerns which might arise in our reduced form empirical specification. From this firm panel we calculate an auxiliary model defined as fifteen reduced form moments $g(\theta)$ which capture essential features of the data, and we pick our four parameters $(\rho, \sigma_\varepsilon, \sigma_\sigma, \sigma_\kappa)$ to best match these simulated moments to their empirical counterparts.

This indirect inference estimation procedure explicitly addresses the concerns identified with the comparative statics exercise: simulated and actual data are treated identically and we use no information from simulated data that is not available in actual data. In addition, we explicitly allow for the presence of multiple simultaneous shocks and formally assess their relative importance.

To construct the empirical moments which comprise our auxiliary model, we first sort months into five bins by their month-level price change standard deviation. We then calculate the relative standard deviation of price changes, the relative MRPT, and the relative frequency for each of the five standard

[44] Previous versions of this paper, which calibrated instead of estimating shocks, also included shocks to the volatility and "common-ness" of exchange rates, to reflect the fact that the Great Recession was a large, common aggregate shock. We found they had little effect. Furthermore, our empirical results control for the volatility of exchange rates and are not driven by the Great Recession. Similarly, we could in principle estimate a different ρ for each aggregate shock, this increase in the parameter space would also render estimation infeasible.

deviation bins.[45] The first five moments test the model's ability to match the time-series variation in price change dispersion observed in the data. The second five moments capture the relationship between this dispersion and passthrough. The final five moments capture the relationship between dispersion and frequency, which we showed can help identify shocks to menu costs from shocks to responsiveness.[46]

Given these 15 moments, we pick our 4 parameters to solve $\widehat{\theta} = \arg\min_{\theta} g(\theta)' W(\theta) g(\theta)$ with positive definite weight-matrix $W(\theta)$.[47] Table 6 shows resulting parameter estimates and measures of model fit.

The main take-away from Table 6 is that we estimate an important role for σ_{ε} but no role for σ_{σ} or σ_{κ}. In fact, even though we allow for simultaneous aggregate shocks to responsiveness, volatility and menu costs, our estimation ultimately prefers a single shock model with only responsiveness shocks. Inspecting standard errors around these point estimates, the model rejects essentially any role for volatility shocks while it allows for some possibility of modest shocks to menu costs. Conversely, versions of the model with no responsiveness shocks are strongly rejected: inspecting the goodness of fit, we can easily reject all models with $\sigma_{\varepsilon} = 0$ in favor of the unrestricted model that allows for such variation.

These numerical results can be seen more easily in Figure 5, which shows the full model fit to each moment as well as that of the restricted model with no responsiveness shocks. Clearly, the model with no responsiveness shocks is unable to match the positive correlation between dispersion and passthrough.[48]

While the bulk of the paper has focused on time-series variation in dispersion, Section 2.4.3 showed similar cross-item patterns. Appendix B.5 thus repeats our indirect inference including permanent cross-item heterogeneity rather than aggregate shocks but delivers similar conclusions. Reassuringly, this is consistent with conclusions in Gopinath and Itskhoki (2010) which arise from matching different facts.

4.4 Interpreting Magnitudes: Implications for Other Observables

Beginning from the steady-state value of $\Gamma = 0.59$, our estimates imply that a one standard deviation decline in responsiveness lowers Γ to 0.43. Interpreting the plausibility of this variation directly is somewhat challenging for two reasons: 1) In reality changes in Γ are likely driven by a variety of mechanisms acting simultaneously so that our estimates of super-elasticity changes are likely standing in as a reduced form for a variety of mechanisms discussed in Appendix B. 2) More importantly, even if one views super-elasticity shocks as the sole source of responsiveness variation, we have no empirical measures of how this elasticity-of-elasticity of demand varies across time to compare our model to. Just measuring the elasticity of demand is difficult much less how it moves with a firm's relative price. We thus instead argue for the plausibility of our estimates by showing that they imply reasonable time-series variation in many economic variables which we *can* measure in the data.

In particular, we show that our model is capable of explaining time-series patterns for the IQR of price changes, overall inflation, import inflation, output growth, frequency and passthrough while also

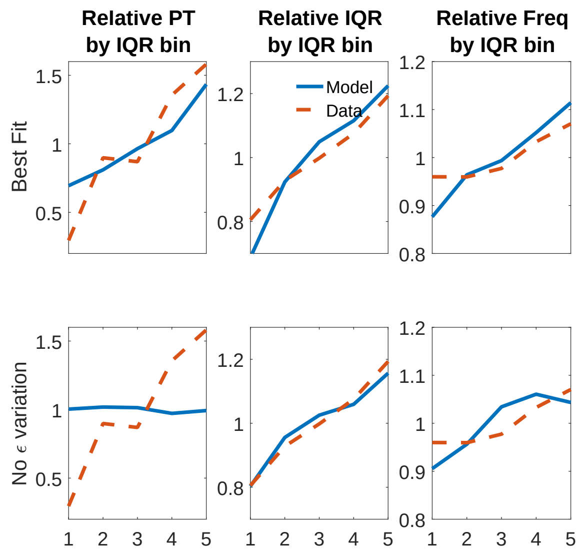
[45] We concentrate on the relative values rather than the absolute values because our benchmark calibration is not perfectly able to match the level of XSD, MRPT and freq. We think of our exercise with shocks as largely about trying to match relative differences across time. Nevertheless, redoing the results using absolute rather than relative moments did not qualitatively change the conclusions but modestly reduces the overall fit of relative movements.

[46] As is standard in indirect inference and in contrast to typical simulated GMM implementations, our auxiliary model need not have any structural interpretation. For example, we have already noted that our OLS MRPT regression will pick up both direct effects of parameters on β as well as indirect effects on covariance terms.

[47] We pick $W(\theta)$ to be the standard efficient weight matrix so that we can apply asymptotic formulas for standard errors but using an identity weight matrix did not change our qualitative conclusions.

[48] More precisely, some parameter configurations with large menu cost shocks can match this relationship, but these parameters are rejected due to an even worse fit to frequency.

Figure 5: Indirect Inference Estimation Results



This figure sorts months into 5 bins by IQR. The left panels show how passthrough varies across these 5 bins, the middle panels show how IQR varies across the 5 bins and the right panels show how frequency varies. Model moments are shown in solid blue and data moments are shown in dashed red. The first row shows results for the best fit estimates of $\rho, \sigma_\varepsilon, \sigma_\sigma, \sigma_\kappa$ and the second row shows the best fit for the restricted model with $\sigma_\varepsilon = 0$. Weights on moment deviations are computed using an estimate of the efficient weight matrix.

generating plausible markup behavior over our 1993-2015 sample period.

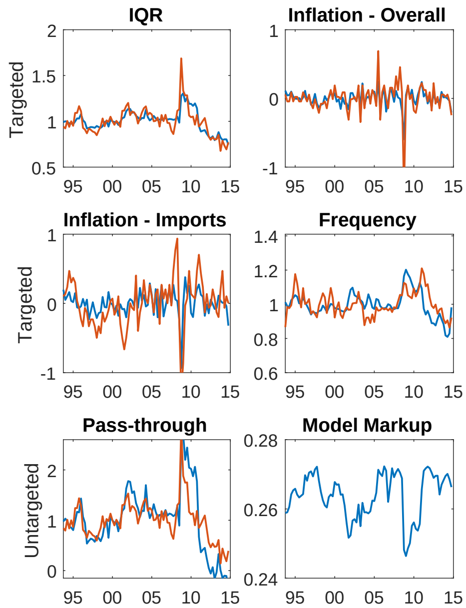
Before describing these results, we must first introduce one additional shock which is necessary for this exercise to be well-defined. In our results thus far we have abstracted from aggregate nominal shocks by assuming total nominal ouptut PC is constant. While this assumption is not important for any of our prior conclusions, it must be relaxed in order to simultaneously match aggregate inflation and output in the data since if nominal output is fixed then inflation and real output growth are perfectly negatively correlated. Following Nakamura and Steinsson (2010), we assume these shocks are iid normal and calibrate their standard deviation to .005 to match the standard deviation of nominal output growth net of real output growth over our 1993-2015 sample period.

Beginning from the ergodic steady-state of the model, we feed the observed sequence of exchange rates from 1993-2015 into the model and then pick the value of the two remaining shocks (ε and nominal output) period-by-period to best fit the IQR of price changes, overall inflation, import inflation, output growth and frequency.[49] Figure 6 shows that we can match these fives series reasonably well with only these two shocks.[50] While there is no standard empirical counterpart for markup variation, we also find that overall markup variation is relatively small, meaning that the super-elasticity shocks necessary to match the other time-series do not imply markup variation which seems unreasonably large. In sum, our parsimonious model provides a good fit to the data along multiple dimensions.

[49]We use the major currencies trade-weighted exchange rate from the IMF. In order to estimate effects beginning from the ergodic distribution, we simulate an initial 10 year burn-in period and average our results over 20 replications

[50]In Appendix B.6 we show results with only responsiveness shocks or only nominal output shocks but not both shocks. With no responsiveness shocks, the model is unable to match IQR, passthrough and frequency, and without nominal output shocks, the model cannot match both inflation and output growth.

Figure 6: Time-Series Fit of Model



Beginning from the ergodic distribution, this figure shows results when we pick exchange rates in the model to match the major currencies trade-weighted exchange rate from 1993-2015 and pick the value of the nominal and responsiveness shock to fit the five targeted series.

5 Conclusion

An active theoretical literature debates whether time-variation in the dispersion of economic variables is driven by changes in the volatility of exogenous shocks or in the endogenous response to shocks of constant size. In this paper, we provide evidence from import prices that variation in responsiveness plays an important role in driving variation in price change dispersion. Using confidential item-level micro price data from BLS import price indices, we document a robust positive relationship between price change dispersion and exchange rate passthrough, both across time and across items. We then estimate a structural price-setting model using indirect inference to match these facts and show it strongly supports variation in responsiveness. This is because increasing responsiveness leads firms to respond more strongly to both idiosyncratic and exchange rate shocks and so increases dispersion and passthrough. In contrast, greater idiosyncratic volatility leads to price changes which are more orthogonal to exchange rate movements, reducing measured passthrough as dispersion rises.

The result that volatility shocks induce a negative relationship between passthrough and dispersion is quite general since it arises from a simple statistical selection effect and so should hold as long as larger shocks increase the probability of price adjustment.[51] Conversely, our assertion that the price data favors time-variation in responsiveness does not depend crucially on our simplifying assumption that this variation arises from changes in the super-elasticity of demand. We adopt this parsimonious specification from Gopinath and Itskhoki (2010), but in Appendix B, we show explicitly that a variety of models which have been used to endogenously generate countercyclical dispersion all share a common

[51] In a Calvo model where frequency is exogenously fixed or in a flexible price model, price adjustment does not rise with volatility. In those models the correlation between dispersion and passthrough is zero, which is still counterfactual.

reduce form representation. In particular, the forces in each of these models give rise to reduced form variation in responsiveness, Γ. While these models were designed in part to endogenously generate time-variation in dispersion, since they do so by changing Γ, they also lead to a positive relationship between dispersion and passthrough. In this sense, one should not interpret our modeling assumption as endorsing or rejecting any particular mechanism which generates endogenous responsiveness. It should instead be interpreted as providing broad support for models with time-varying responsiveness.

Finally, it is important to reiterate the caveat in the introduction that our analysis is focused solely on import prices. However, there is a limited but growing body of research arriving at similar conclusions in other contexts. We focus on imports since we measure shocks to costs using exchange rate movements. However, our methodological insight, that the joint behavior of passthrough and dispersion can be used to differentiate changes in volatility from changes in responsiveness, should apply to shocks other than exchange rates and outcomes other than prices. This means that with different microdata, a similar exercise could be performed studying the passthrough of any well-identified aggregate or sectoral shock into any outcome variable of interest and how that relates to the dispersion of that variable. We think it is an interesting avenue for future research to extend our analysis to variety of shocks such as credit, energy price, or monetary shocks identified using high frequency financial data and to explore passthrough into a variety of endogenous outcomes.

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Table 1: Relationship Between passthrough and Dispersion

	(1) Overall	(2) IQR	(3) IQR+Freq	(4) IQR+All Ctrls	(5) XSD	(6) XSD+Freq	(7) XSD+All Ctrls
Δe	0.154	0.143	0.143	0.174	0.141	0.141	0.176
	(0.012)	(0.011)	(0.011)	(0.015)	(0.012)	(0.012)	(0.015)
IQR×Δe		0.070	0.070	0.050			
		(0.009)	(0.009)	(0.009)			
IQR		-0.002	-0.002	-0.002			
		(0.001)	(0.001)	(0.001)			
XSD×Δe					0.058	0.058	0.038
					(0.009)	(0.009)	(0.009)
XSD					-0.002	-0.002	-0.002
					(0.001)	(0.001)	(0.001)
Freq×Δe			0.010	0.019		0.012	
			(0.009)	(0.009)		(0.009)	
Freq			0.004	0.004		0.004	
			(0.001)	(0.001)		(0.001)	
All Ctrls	No	No	No	Yes	No	No	Yes
Num obs	129260	129260	129260	129260	129260	129260	129260
R^2	0.035	0.038	0.039	0.040	0.037	0.038	0.039

"All controls" are frequency of adjustment (freq), frequency of product substitutions (subs), freq and subs×Δe, gdp growth, gdp growth×Δe, SDe, SDe×Δe, month dummies, month dummies×Δe, t, t×Δe, Δ cpi, Δus gdp, Δuscpi. All regressions have country×PSL fixed effects and standard errors are clustered by country×PSL. Primary Strata Lower (PSL) 2 to 4-digit harmonized codes defined by BLS. Dispersion and freq results standardized so that coefficients give a one-standard deviation effect. Sample period: Oct 1993-Jan 2015.

Table 2: Relationship Between passthrough and Dispersion, Excluding Great Recession

	(1) Overall	(2) IQR	(3) IQR+Freq	(4) IQR+All Ctrls	(5) XSD	(6) XSD+Freq	(7) XSD+All Ctrls
Δe	0.129	0.131	0.132	0.159	0.128	0.129	0.160
	(0.012)	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)	(0.014)
IQR×Δe		0.037	0.038	0.027			
		(0.011)	(0.011)	(0.012)			
IQR		0.003	0.004	0.004			
		(0.001)	(0.001)	(0.001)			
XSD×Δe					0.015	0.016	0.009
					(0.009)	(0.009)	(0.009)
XSD					0.003	0.003	0.003
					(0.001)	(0.001)	(0.001)
Freq×Δe			0.014	0.024		0.013	0.024
			(0.009)	(0.010)		(0.009)	(0.010)
Freq			0.004	0.004		0.004	0.004
			(0.001)	(0.001)		(0.001)	(0.001)
All Ctrls	No	No	No	Yes	No	No	Yes
Num obs	119816	119816	119816	119816	119816	119816	119816
R^2	0.034	0.035	0.036	0.037	0.035	0.036	0.037

"All controls" are frequency of adjustment (freq), frequency of product substitutions (subs), freq and subs×Δe, gdp growth, gdp growth×Δe, SDe, SDe× Δe, month dummies, month dummies× Δe, t, t×Δe, Δ cpi, Δ us gdp, Δ uscpi. Regressions have country×PSL fixed effects and standard errors are clustered by country×PSL. Dispersion and frequency results are standardized so that coefficients give a one-standard deviation effect. Sample period: Oct 1993-Jan 2015, excluding price changes from Dec 2007-Jun 2009.

Table 3: Sectoral vs. Aggregate Dispersion Effects

	(1) IQR_{sector}	(2) IQR_{sector}+ $IQR_{overall}$	(3) IQR_{abs_dev}	(4) $IQR_{\%\_dev}$	(5) IQR_{sector}+ Month dummy × Δe
Δe	0.184	0.174	0.193	0.187	-0.050
	(0.015)	(0.015)	(0.014)	(0.015)	(0.104)
IQR_{sector} × Δe	0.038	0.025			0.024
	(0.011)	(0.011)			(0.011)
IQR_{sector}	-0.003	-0.002			-0.001
	(0.001)	(0.001)			(0.001)
$IQR_{overall}$ × Δe		0.040			
		(0.009)			
$IQR_{overall}$		-0.001			
		(0.001)			
IQR_{abs_dev} × Δe			0.026		
			(0.011)		
IQR_{abs_dev}			-0.001		
			(0.001)		
$IQR_{\%\_dev}$ × Δe				0.030	
				(0.012)	
$IQR_{\%\_dev}$				-0.001	
				(0.001)	
Month Dummy	No	No	No	No	Yes
Month Dummy×Δe	No	No	No	No	Yes
All Ctrls	Yes	Yes	Yes	Yes	Yes
Num obs	129232	129232	129232	129232	129232
R^2	0.040	0.040	0.039	0.039	0.067

"All controls" are frequency of adjustment (freq), frequency of product substitutions (subs), freq and subs× Δe, gdp growth, gdp growth × Δe, SDe, SDe × Δe, month dummies, month dummies × Δe, t, t x Δe, Δ cpi, Δ us gdp, Δ uscpi. $IQR_{\text{sector,t}}$ is the month-level interquartile range of an item's broad section group in month t. $IQR_{\text{overall,t}}$ is month-level interquartile range across all items in month t. $IQR_{\text{deviation,t}} = IQR_{\text{sector,t}} - mean(IQR_{\text{sector,t}})$ is the absolute deviation of the IQR in an item's sector from the average IQR across all sectors in month t. $IQR_{\text{relative,t}} = IQR_{\text{sector,t}}/mean(IQR_{\text{sector,t}})$ is the percentage deviation of the IQR in an item's sector from the average IQR across all sectors in month t. See text for additional description. All regressions have country x PSL fixed effects and robust standard errors are clustered at the country x PSL level. Dispersion and frequency results are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table 4: Robustness to Misspecification

	(1) Full Inter-action	(2) IQR+ IQR^2	(3) Δe+ Δe^2	(4) Δe+ l. Δe	(5) Δe+ l. Δe+ l2. Δe	(6) Δe>0	(7) Δe<0	(8) 5+chgs	(9) <=5 chgs	(10) Median Regs
Δe	0.158	0.164	0.188	0.239	0.265	0.168	0.178	0.199	0.098	0.163
	(0.014)	(0.015)	(0.015)	(0.035)	(0.039)	(0.020)	(0.018)	(0.017)	(0.014)	(0.010)
IQR $\times\Delta$e	0.026	0.032	0.066	0.076	0.073	0.054	0.037	0.060	0.024	0.029
	(0.009)	(0.011)	(0.012)	(0.022)	(0.026)	(0.014)	(0.014)	(0.011)	(0.013)	(0.006)
IQR	0.001	0.001	-0.002	-0.002	-0.002	-0.004	-0.000	-0.003	0.003	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IQR$^2\times\Delta$e		-0.004								
		(0.005)								
IQR^2	-0.004	-0.005								
	(0.000)	(0.000)								
IQR$\times\Delta$e^2			0.057							
			(0.022)							
Δe^2	-0.012		0.059							
	(0.022)		(0.023)							
IQR$\times$l.Δe				0.070	0.074					
				(0.019)	(0.030)					
l.Δe				0.065	0.086					
				(0.014)	(0.027)					
IQR$\times$l2.Δe					0.032					
					(0.025)					
l2.Δe					0.063					
					(0.018)					
All Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num obs	129260	129260	129260	57589	42127	62551	62297	114141	28014	129260
R^2	0.044	0.044	0.041	0.025	0.028	0.049	0.057	0.029	0.095	

"All controls" are frequency of adjustment (freq), frequency of product substitutions (subs), freq and subs$\times$ Δe, gdp growth, gdp growth $\times$ Δe, SDe, SDe $\times$ Δe, month dummies, month dummies $\times$ Δe, t, t x Δe, Δ cpi, Δ us gdp, Δ uscpi. l.Δe and l2.Δe are the cumulative exchange rate movement in the lagged and twice lagged price spell, respectively. See text for additional description. All regressions have country $\times$ PSL fixed effects and robust standard errors are clustered at the country $\times$ PSL level. Dispersion and frequency results are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table 5: Parameter Values

Parameter	Symbol	Menu Cost Model	Source
Discount factor	β	$0.96^{1/12}$	Annualized interest rate of 4%
Fraction of imports	$\omega/(1+\omega)$	14.5%	BEA input-output table
Cost sensitivity to ER shock			
Foreign firms	α	0.165	Estimation (see text)
U.S. firms	α^{US}	0	
Menu cost	κ	5.0%	Estimation (see text)
Markup elasticity	ε	2.35	Estimation (see text)
Demand elasticity	σ	5	Broda and Weinstein (2006)
Std. dev. exchange rate shock, e_t	σ_e	2.5%	Match bilateral RER
Idiosyncratic productivity process, a_t			
Std. dev. of shock	σ_A	8.6%	Estimation (see text)
Persistence of shock	ρ_A	0.85	Gopinath and Itshkoki (2010)

Table 6: Estimated Parameters and Fit

Parameter	Estimate	95% Confidence Interval	
σ_ε	0.365	(0.347,0.383)	
σ_σ	0.000	(0.00,.0053)	
σ_κ	0.014	(0.00,.0337)	
ρ	0.845	(0.838,0.852)	

Models	Wald-Statistic/Likelihood Ratio	95% Critical Value	99% Critical Value
Unrestricted Model	41.64	19.68	24.72
$\sigma_\varepsilon = 0$	113.2851	3.84	6.64

Asymptotic s.e.'s for parameters in parantheses. Unrestricted model Wald-Statistic: $g\left(\widehat{\theta}\right)' W\left(\widehat{\theta}\right)' g\left(\widehat{\theta}\right) \sim \chi^2(11)$

Restricted models: $2\left[g\left(\widehat{\theta}_r\right)' W\left(\widehat{\theta}_u\right)' g\left(\widehat{\theta}_r\right) - g\left(\widehat{\theta}_r\right)' W\left(\widehat{\theta}_u\right)' g\left(\widehat{\theta}_r\right)\right] \sim \chi^2(1)$

.

Online Appendix Materials - Not For Print

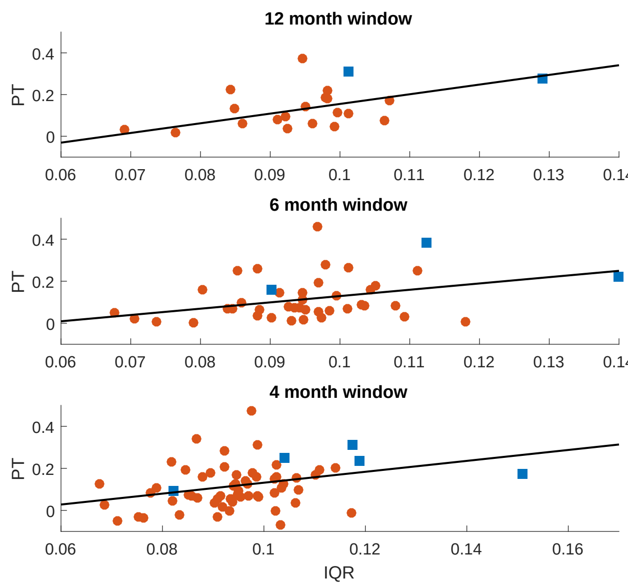
A Empirical Appendix: Online Only

A.1 Additional Empirical Results

In this section, we provide a number of robustness checks and extensions of our primary analysis.

Figure A.1 replicates Figure 2 using alternative window lengths and shows that we continue to find a strong positive relationship between our non-parametric passthrough estimates and dispersion which arises both including and excluding the Great Recession.

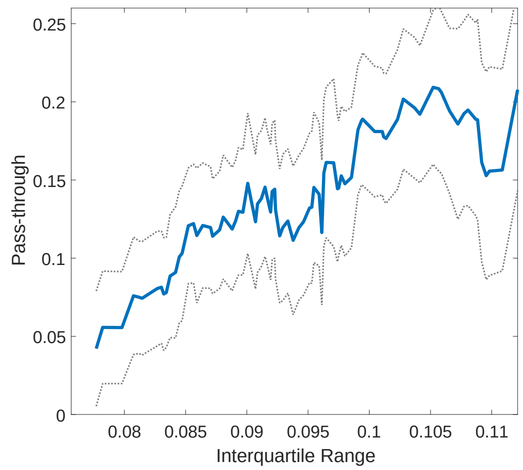
Figure A.1: Dispersion vs. passthrough: Different Windows



This figure shows the IQR of all non-zero price changes against our preferred measure of exchange rate passthrough, described below. Both statistics are computed separately in a series of disjoint windows which span our sample period. Our primary specification in the text uses 8 month windows, but this figure shows results are similar for 4, 6 and 12 month windows. Windows which have a majority of months during the Great Recession, as defined by NBER, are shown in blue. The black regression line includes all observations while the red-dotted line excludes Great Recession observations.

Figure A.2 repeats the binned time-series regression in Figure 3 using a much larger number of bins. This allows for a more non-parametric relationship between passthrough and dispersion and again shows that the linearity assumed in most of our empirical regressions is a reasonable approximation of the data. Unsurprisingly, there is somewhat more noise when performing this exercise, but the basic picture is unchanged.

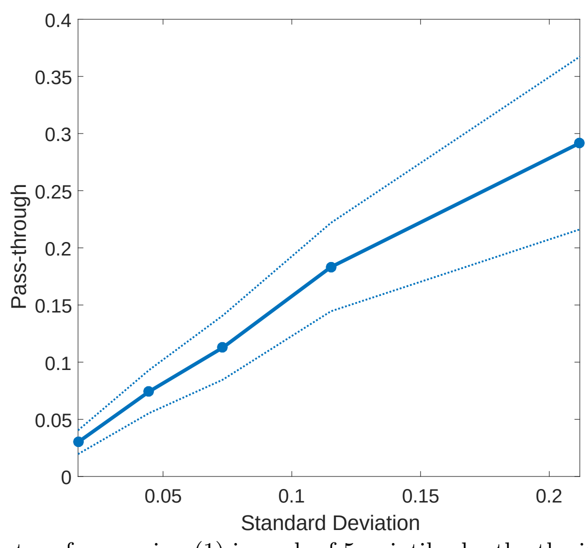
Figure A.2: Non-Parameteric IQR-passthrough Relationship



This figure shows separate estimates of regression (1) in each of 80-intervals by months' IQR. The first point includes observations from months with IQR in percentiles 1-20, the second observation months in percentiles 2-21, up to the last observation which includes observations from months in percentiles 80-100. All regressions have country $\times$ PSL fixed effects and robust standard errors are clustered at the country $\times$ PSL level. We also include controls for foreign CPI growth, US gdp growth and US CPI growth. 95% confidence intervals are shown with dotted lines, and the average IQR in each window is shown on the x-axis.

Figure A.3 repeats the binned time-series regression in Figure 3 instead using cross-item dispersion. In particular, we sort individual items by their item-level standard deviation into 5 quintiles and then run regression 1 separately in each bin. This shows that there is a positive relationship between item-level dispersion and passthrough using a specification that does not impose linearity like in Table A5.

Figure A.3: Item-Level Dispersion-passthrough Relationship



This figure shows separate estimates of regression (1) in each of 5-quintiles by the the item-level standard deviation of price changes. All regressions have country $\times$ PSL fixed effects and robust standard errors are clustered at the country $\times$ PSL level. We also include controls for foreign CPI growth, US gdp growth and US CPI growth. 95% confidence intervals are shown with dotted lines, and the average item-level standard deviation value in each quintile is shown on the x-axis.

In Table 1, Columns (4) and (7), we showed that despite the fact that dispersion is countercyclical, our patterns indeed reflect a passthrough-dispersion relationship and are not just proxying for a passthrough-business cycle relationship. In that table, we measured the business cycle using real GDP growth, but one might be concerned that real GDP growth is only a partial proxy for the business cycle. Table A1 shows that our conclusions are robust to instead measuring the business cycle using NBER Recession indicators or using HP filtered log GDP instead of gdp growth. These results show that passthrough is indeed countercyclical (at least when measuring cyclicality using real GDP growth or business cycle dates), but that this does not drive our dispersion effects. The effects of dispersion on passthrough are very similar after controlling for business cycle effects.

One might also be concerned that our results could be driven by compositional effects as the mix of product-origin countries and bilateral exchange rates varies across time. Table A2 shows that this is not the case by redoing our results restricted to particular countries/country groups.[52] These compositional concerns are more of a concern for our cross-item effects than our time-series results since an item's country of origin is necessarily fixed across time. Thus, we also repeat our cross-item results for individual countries in Table A6.

In order to use a comprehensive sample, our baseline results include a broad set of items, described in Section 2.1. However, many of these products have less product differentiation or pricing power and so are likely less well described by our theoretical price-setting model. In Table A3 we also show that our results continue to go through when using a narrower set of manufactured products that map more naturally to our model.

Finally, as an additional check of misspecification as well as the importance of our sample selection, Table A4 shows our results using an alternative passthrough specification which does not specifically condition on adjustment. More specifically, we simply regress Δp on Δe plus various additional controls and interactions over various time-intervals, without conditioning on adjustment. For example, in column 1 we simply regress the one month change in price on the one month change in exchange rates, and items in this interval may have either zero or 1 price change. In column 4 we regress one-year changes on one-year changes and item in the regressions may thus have between 0 and 11 price changes in this interval. This specification is more akin to the long-run passthrough measures in Gopinath and Itskhoki (2010). It is less useful for identification purposes but is useful for checking the robustness of our sample selection and for diagnosing misspecification. This is because it can be computed for items with a single price change, in contrast to our primary passthrough measure which can only be computed for items with at least two price changes.[53] Thus, sample sizes are expanded in this specification and we can include items with fewer price changes.

A.2 Additional Sample Summary Statistics

This section provides additional detail on the construction of our benchmark empirical sample and various related summary statistics. From our raw data which includes 2,527,619 price observations from October, 1993 – January, 2015, we begin by dropping the 203,562 price observations which are imputed and so flagged as "unusable" observations by the BLS. Row 1 of Table A7 shows the total number of price observations and items as well as various summary statistics of the raw data after dropping these unusable prices. The typical product is in the data set for a little over 3 years and changes prices roughly 9 times.

[52] There are not enough imports from individual countries aside from Mexico and Canada to get precise individual country estimates.

[53] We require at least one price change so that we can correctly measure Δe. For items with no price changes, exchange rate movements are left-censored and cannot be accurately measured. Nevertheless, despite the concerns with this measure, repeating results simply using the cumulated exchange rate change since an item enters the BLS sample allows us to further expand our sample to include all items and delivers similar results.

The last 3 columns show the 25th, median and 75th percentile of non-zero price changes. From this raw data, we then exclude commodities, intrafirm transactions and non-dollar prices in our baseline sample. We exclude non-dollar prices because these items mechanically have passthrough of 1 when not adjusting prices and so cannot be used to measure responsiveness. This means, they contain no useful information for our identification purposes. Similarly, commodities exhibit extremely high competition and are undifferentiated. This means they also exhibit nearly 100% passthrough at all times and so cannot be used to measure variation in passthrough across time. Finally, we exclude intrafirm transactions and keep only arms-length price transactions. This is because intrafirm transactions are not necessarily allocative since these transfer prices are often set for tax purposes or other internal purposes and do not necessarily have any relationship to market values so they have little value for our analysis. In total, excluding these prices, which are not informative for our analysis, reduces our sample size substantially. However, of the 1,135,439 observations dropped, the vast majority, 923,978, are intrafirm transactions. This means that although our sample size drops substantially, this is largely just from dropping prices which are essentially mismeasured relative to their allocative value. Overall, this sample selection criteria is identical to the initial sample restriction in Gopinath and Itskhoki (2010), and so makes our results more comparable to the existing literature.

Furthermore, it is important to note that our goal is not to inform aggregate statistics with our analysis. So it is not important that our sample be representative of the overall composition of import price indices. Our goal is to instead use a subset of our data to provide sharp identification, and for these purposes it makes sense to focus on the subset of data most suited for this purpose, even if it does not necessarily aggregate up to national statistics as closely as broader data sets might.

The more relevant comparison is between this initial sample cleaning and our final analysis sample, which includes only observations with at least two price changes. Comparing row 2 and 3 shows that products in our analysis sample have slightly longer average lives in the data set. This is not surprising since items which are only in the data set briefly are less likely to have measured price changes. Even less surprising, the average number of price changes per item is higher in our analysis sample, but this will mechanically be the case since this is how we are selecting our sample. However, the distribution of price changes conditional on adjustment is essentially the same. Overall these comparisons reassure us that we are not performing our analysis on a particularly unusual subset of data. Again, it is worth noting the relationship between our final sample and that in Gopinath and Itskhoki (2010). Our sample is identical to theirs except that we require items to have 2+ price changes while they require items to have only 1+ price changes because MRPT can only be measured for items with two completed price spells while their LRPT measure can be computed for items with only a single price change. However, Appendix Table A4 shows results for alternative specifications that allow us to include items with 1+ price changes. These specifications are less useful for identification purposes but are useful for checking the robustness of our sample selection and for diagnosing misspecification, and overall we find similar patterns.

B Modeling Appendix: Online Only

B.1 Interpretation of Responsiveness Fluctuations

We refer to responsiveness, Γ, as anything that affects the elasticity of a firm's desired price to a cost shock. What economic forces generate time-series variation in this responsiveness parameter? In this section, we show that many of the proposed mechanisms put forward independently to explain countercyclical dispersion, such as ambiguity aversion, customer search, employer learning and experimentation, also map into this responsiveness parameter in a way that has not previously been noted. Conversely, we show that the other dominant mechanism (other than Kimball demand) used by the international finance literature to generate incomplete passthrough – variation in market power, implies a positive relationship between passthrough and dispersion. As a result, all of these mechanisms have similar implications for the relationship between passthrough and dispersion that is at the heart of our paper.

B.1.1 Mechanisms Which Have Been Used to Explain Time-Varying Dispersion

Ambiguity Aversion

Ilut et al. (2014) show that concave hiring rules (which they microfound using an information processing framework where agents are ambiguity averse but which could result from asymmetric adjustment costs) endogenously generate higher cross-sectional (employment) dispersion and shock passthrough during recessions.

It is easy to illustrate the basic mechanism and to see how it naturally maps into responsiveness. Assume firms receive a signal s about future productivity and that the signal has an aggregate and idiosyncratic component, $s = a + \epsilon$, where the idiosyncratic shock ϵ is mean zero and i.i.d. across firms and across time. Further assume, as Ilut et al. (2014) do, that all firms follow the same decision rule, $n = f(s)$, where n is net employment growth and $f(s)$ is strictly increasing and concave. This implies that firms exhibit asymmetric adjustment to shocks: firms respond more to a signal of a given magnitude during recessions than during booms because during recessions firms are in the more concave region of their policy function. As parts 2 and 3 of Proposition 1 in Ilut et al. (2014) prove, this implies that the dispersion of employment changes is higher in recessions.

Concave policy rules also imply that aggregate employment growth is more responsive to aggregate shocks (e.g. higher cost passthrough) in recessions than booms. Formally, for any two realizations of the aggregate shocks with $a' > a$,

$$\frac{d}{da}E[n|a] > \frac{d}{da'}E[n|a'],$$

which follows directly from the strict concavity of $f(s)$. (The formal proof is given in part 1 of Proposition 1 in Ilut et al. (2014)). Thus, a positive correlation between higher dispersion and higher passthrough is a direct implication of concave policy rules.

There is a natural mapping between this mechanism and our responsiveness measure. To see this, take a first order Taylor approximation of $f(s)$ around the steady state values of a and ϵ:

$$\begin{aligned} n = f(a, \epsilon) &\approx f(\bar{a}, \bar{\epsilon}) + f_a(a - \bar{a}) + f_\epsilon(\epsilon - \bar{\epsilon}) \\ &\approx f(\bar{a}, 0) + f_a \Delta a + f_\epsilon \epsilon. \end{aligned}$$

where f_a and f_ϵ are the partial derivatives with respect to a and ϵ respectively evaluated at $\bar{a}$ and $\bar{\epsilon}$. To get from line 1 to 2 we have used the fact that the idiosyncratic shock has mean zero. Since f

is concave, these partial derivatives are positive and their magnitude governs how much the aggregate and idiosyncratic innovations affect employment growth. Comparing the above equation to our flex price equation for price changes (4), we see there is a tight connection. In particular, if we abstract from variation in alpha, there is an inverse relationship between responsiveness and the slope of $f(s)$: $1+\Gamma = \frac{\alpha}{f_a}$.

The intuition for this connection is simple: during booms, firms are in the flat region of their concave policy function where they have a low responsiveness to shocks of a given size (e.g. Γ is relatively large) . However, in recessions firms are in the steep part of their policy functions and endogenously respond more to shock of the same size (e.g. Γ is relatively small).[54] In sum, any mechanism that generates concave policy rules as a function of the firms shocks is naturally going to generate countercyclical dispersion and a positive correlation between passthrough and dispersion.

Learning

Baley and Blanco (2016) present a price-setting model with menu costs and imperfect information about idiosyncratic and aggregate productivity. They use this model analyze how price setting behavior is shaped by changes in information by analyzing the response to random increases in "uncertainty", in which firms become less informed about their underlying costs (but with no actual change in current idiosyncratic or aggregate productivity and with no changes in their volatility). That is, they study the response to a pure shock to information in which firms become less informed about their current level of productivity.

The basic logic of their model is simple to understand. Upon the arrival of a new uncertainty regime, a firm's uncertainty increases and then quickly decreases as the firm learns about the shocks they are facing. These informational shocks in turn lead to an increase in price dispersion, as proved in Baley and Blanco (2016) Proposition 6.

Is cost passthrough higher after information shocks? In order to gain intuition, it useful to examine how the level of firm's uncertainty about costs, Ω_t, affects firms incentive to learn about its markup, μ_t around a short interval of time Δ:

$$\Delta\mu_{t+\Delta} = \left(\frac{\gamma}{\Omega_t+\gamma}\right)\mu_t + \left(\frac{\Omega_t}{\Omega_t+\gamma}\right)(s_{t-}s_{t-\Delta})$$

Firms update their guess of the new markup (which affects the optimal price it would like to set) as a convex combination of a weight on its previous markup and and a weight on the new information from its signals, s_t. Here γ captures the size of the information friction. It is obvious that when information is low and firms are more uncertain about their costs, they (optimally) put more weight on new information. This increases the speed of learning about the new monetary shocks hitting the economy and increases the level of passthrough. Baley and Blanco (2016) show that this implies that passthrough is higher for monetary shocks.

[54] Ilut et al. (2014) show empirically that for the U.S. manufacturing data that both employment dispersion and passthrough are higher in recessions. For passthrough, they estimate hiring rules both non-parametrically and parametrically and find higher passthrough to shocks of the same size in recessions for both rules. In particular, for the non-parametrically estimated hiring rule (see their Figure 6), the average response in boom to a 2 SD shock was +0.16% while the average response in recession to a 2 SD shock was -0.55%. These standard deviation values are calculated over the entire sample, so this shows that the response to a shock of the same size is larger in recessions. For the parametric hiring rule (see Column (I) in their Table 8), the average response in boom was +0.31% while the average response in recession was -1.05%.

The intuition is simple. The response to monetary shocks is increasing in firms' information about the size of shocks. Since we already established that a decline in information quickens the speed of learning, in the sense that agents put relatively more weight on new signals, this means that firms put more (Bayesian) weight on the new, monetary policy shock and passthrough rises. Thus, their model implies a positive relationship between price change dispersion and passthrough of cost shocks. Baley and Blanco (2016) in fact devote an entire section of their paper to showing that this mechanism is economically important in their calibrated model (see Table 4 in Section 6) and induces variation in dispersion and passthrough that lines up with the empirical facts we document in Section 2.3.

The firm learning mechanism maps precisely into our responsiveness measure: variation in responsiveness corresponds to (endogenous) variation in the speed of firm learning in response to information shocks. When firms have less information, they respond by learning more quickly about the aggregate shocks they face, increasing the responsiveness of their prices to aggregate shocks and increasing price dispersion as they respond more aggressively to idiosyncratic shocks of constant size.

Consumer Search

A growing body of research highlights the importance of changing consumer shopping behavior for business cycle outcomes. For example, Kaplan and Menzio (2016) generate business cycle fluctuations from changes in "market competitiveness". Unemployed workers spend less and search more for low prices than employed workers, so increases in unemployment increase competition. This increased competition increases incentives for firms to further reduce employment. This feedback between employment and competition can lead to self-fulfilling fluctuations and so endogenously give rise to recessions.

This mechanism is supported by a growing empirical literature. Aguiar, Hurst, and Karabarbounis (2013) document that households search more during recessions. Stroebel and Vavra (2016) show that firms adjust markups in response to changing customer price sensitivity over house price booms and busts. Munro (2016) uses UPC level panel data to show that, consistent with a changing demand elasticity story, dispersion of stores' growth rates increases during recessions and this increase is larger in markets where the increase in consumer shopping effort is highest.

Time-variation in the elasticity of demand naturally maps into our responsiveness framework. Recall, that the steady state level of responsiveness in our model is given by $\Gamma = \frac{\varepsilon}{\sigma-1}$. Thus as long as there is any adjustment of markups in response to shocks ($\varepsilon > 0$), then if certain periods of time such as recessions are characterized by increased competition (because consumers search more), with larger σ and lower markups, they will also be times of greater responsiveness and thus price change dispersion and cost passthrough.[55]

Indeed Munro (2016) explicitly explores the link between changes in the elasticity of demand (coming from variations in consumer search behavior over the cycle) and countercyclical dispersion. The intuition is straightforward: If consumers spend more time shopping for lower prices during recessions in order to smooth consumption, then firms face more elastic demand during recessions. This means that firm sales are more responsive to a given size cost shock leading to higher dispersion of firm sales and employment in recessions. Munro (2016) formalizes this mechanism in a simple business cycle model where search

[55]The presence of markup adjustment can be induced by a wide-variety of strategic-complementarities and is a pervasive assumption. In the passthrough literature this assumption is used explain incomplete passthrough and in the monetary literature it is used to explain large and persistence responses to monetary shocks.

frictions in product markets provide a role for consumer search effort to affect the elasticity of demand that firms face and shows that it generates quantitatively important fluctuations in dispersion even with no changes in the volatility of shocks.

Experimentation

Bachmann and Moscarini (2012) was one of the first papers to explore whether the increase in both macro and micro dispersion was a result of larger shocks or whether causation ran in the opposite direction. In particular, they explore whether time-varying price experimentation in response to negative aggregate shocks can explain countercyclical price dispersion dispersion in both the time-series and the cross-section of individual outcomes.

Bachmann and Moscarini (2012) start by adding imperfect information about demand to an otherwise standard monopolistically competitive model. The basic idea is that firms are heterogeneous in their elasticity of demand but face idiosyncratic demand shocks and so only gradually learn from sales about this elasticity. During booms, price dispersion is low as firms understand the demand curve they face and the cost of deviating from the average price is large in terms of lost profits. However, in recessions, when the chance of bankruptcy is high, they show that the chance that firms will choose to experiment increases because the opportunity cost of price mistakes is lower and the chance of going out of business is higher. Thus, the model delivers countercyclical price dispersion without time-varying volatility shocks.

Their model also implies that passthrough is higher when experimentation is higher. To see this, consider a recession induced by a negative TFP shock. For the firm, this decrease in TFP is a negative cost shock that increases the probability of firm exit and incentive to experiment. Bachmann and Moscarini (2012) show that in this situation the firm will choose to experiment by raising its price, and the size of the price increase is decreasing in firms expectations of future demand. The logic is simple. If the firm does not change its price, it is more likely to go out of business soon, because it likely can no longer cover its costs (this is all probabilistic, based on its beliefs about demand). In principle, it could reduce the price, hoping that true demand is so elastic that revenues will boom, however, if such a high elasticity was plausible then it would have already lowered its price during the boom when the firm was confident demand was high and it could earn large profits.[56] So the only possible move is to raise the price. This generates twin benefits as it increases the chance of survival and also provides information about the demand curve. While firms can experiment at any time, it is not profitable to do so during booms when costs are low and revenues are high and becomes profitable when costs rise in recessions. Hit by these negative cost shocks, firms then choose to experiment in the direction that at least offsets costs. In addition, more pessimistic firms raise their prices by a larger amount than firms with strong beliefs about demand (see Figure 3 in Bachmann and Moscarini (2012)). This means that pessimistic firms have higher passthrough on average than optimistic firms.

Finally, recessions lead to an increase in the mass of pessimistic firms near exit. Since pessimistic firms experiment more and have higher passthrough, this implies that both passthrough and price dispersion rise. Thus variation in the incentive to experimentation acts just like time-varying responsiveness in our baseline framework: both mechanisms generate higher price dispersion and higher passthrough during recessions.

[56]The logic is based on the envelope theorem. The first-order expected revenue gain from reducing the price cannot be large enough to more than offset the cost increase, because otherwise the previous price could not have been optimal.

B.1.2 Mechanisms Which Have Been Used to Explain Incomplete passthrough

In a recent survey of the passthrough literature (Burstein and Gopinath (2014)), they show that a number of mechanisms aside from Kimball demand map into our responsiveness parameter, $\mathit{\Gamma}$. Variation in markups arising from variation across firms' in their respective market power is the most common alternative to Kimball demand in the passthrough literature. Canonical references are Krugman (1986), Helpman and Krugman (1987), Dornbusch (1987) and more recently Atkeson and Burstein (2008). Since the body of our paper shows extensive results for Kimball demand, we focus here on this market power alternative and show that it also implies a positive correlation between passthrough and price dispersion. To be consistent with the rest of our paper, we focus on time-variation in market power though across firm variation generates similar predictions.[57]

Variation in Market Power

In this setting a discrete number of products and strategic complementarity gives rise to variable markups and markup elasticity, $\mathit{\Gamma}$, in the same form as our baseline model. The difference is that $\mathit{\Gamma}$ is determined by different parameters: variation in market power and elasticities of demand and whether there is Bertrand or Cournot competition rather than from kinked demand. Otherwise the underlying structure of the problem is the same. See Section 4.2 of Burstein and Gopinath (2014), which itself builds on Atkenson and Burstein (2008) for full details.[58] We now show that variation in Γ, coming from underlying time-variation in competititive pressure, induces a positive correlation in passthrough and price dispersion.

Despite a similar overall structure, since there are a finite number of firms and strategic complementarity, we must check whether the indirect effect of the exchange rate change coming through changes in other firms' prices overturns the basic results in Section 4. As in our baseline model, price changes depend on changes in the exchange rate, idiosyncratic shocks and changes in the overall price index:

$$\Delta p_i = \frac{\alpha \Delta e + \mathit{\Gamma} \Delta p + \epsilon_i}{1 + \Gamma}$$

Averaging across firms (across i) at a moment in time gives a simple expression for passthrough::

$$\frac{\Delta p_i}{\Delta e} = \frac{\alpha}{1+\Gamma} + \frac{\Gamma}{1+\Gamma}\frac{\Delta p}{\Delta e}$$

Next, do a comparative static with respect to Γ since this captures in a simple way how changes in market power affect passthrough:

[57] This differentiates our paper from the previous literature as it focused on variation across firms.

[58] Here we give just a flavor. Final sector output is modeled as a CES of the output of a continuum of sectors with elasticity of substitution η and sector output is CES over a finite number of differentiated products with elasticity ρ, where $1 \leq \eta \leq \rho$. They show that this implies that $\Gamma = \frac{s_i(\rho-\eta)(\rho-1)}{(\eta s_i+\rho(1-s_i))(\eta s_i+\rho(1-s_i)-1)}$ under Bertrand and $\Gamma = (\rho-1)(\frac{1}{\eta} - \frac{1}{\rho})\mu_i s_s$ under Cournot. Thus, (time) variation in Γ is induced by (time) variation in η or all market shares s_i. The latter effect would come through firm entry. One can show that in both models Γ is increasing in s_i (i.e. less competition due to less entry) and decreasing in η (higher values mean market is closer to perfect competition). Thus variation in market power can generate variation in Γ.

$$\frac{\partial \frac{\Delta p_i}{\Delta e}}{\partial \Gamma} = -\frac{\alpha}{(1+\Gamma)^2} + \frac{1}{(1+\Gamma)^2}\frac{\Delta p}{\Delta e}$$
$$= \frac{\frac{\Delta p}{\Delta e} - \alpha}{(1+\Gamma)^2} < 0 \text{ if } \alpha > \frac{\Delta p}{\Delta e}$$

In general, passthrough is decreasing in Γ if general equilibrium effects are not too strong, and these effects are largely determined by the magnitude of Γ. A larger Γ means that individual prices are more sensitive to changes in the aggregate price level because strategic complementarities are stronger. As long as $\alpha > \frac{\Delta p}{\Delta e}$, the GE effect is dominated by the first term and passthrough is decreasing in Γ. This is the most relevant case since the case in which GE dominates requires passthrough to the overall price level to be bigger than the direct effect on individual prices since α is an upper bound on the direct effect.

Under the precise details of the market power model, the upper bound on the GE effect is α and under most conditions is strictly less than that. In particular, this relationship holds if firms face slightly different exchange rates. This could happen if competing firms within the same industry source inputs from different countries. Define firm $j's$ common exposure to all other firm exchange rate variation as $\Delta e_j = \theta\Delta e + (1-\theta)\Delta v_j$ with $\Delta v_j \perp \Delta e$ for all j. If $\theta = 1$ then firm j is exposed to the same exchange rate variation as all other firms and if $\theta = 0$, there is no common exchange rate variation. The most interesting case is if $0 < \theta < 1$ where there is some difference in exposure to the exchange rate between firm i and firm j. In this case we can easily show (after some patient algebra) that passthrough is decreasing in Γ just as in our baseline case as long as $0 < \theta < 1$ (and $0 < w_i < 1$ but this by construction).[59] In particular,

$$\frac{\partial\left(\frac{\Delta p_i}{\Delta e}\right)}{\partial \mathit{\Gamma}} = \frac{\alpha\left((1-\theta)(1+\mathit{\Gamma})\mathit{\Gamma}\frac{\partial w_i}{\partial \mathit{\Gamma}} + (\theta + (1-\theta)w_i - 1)\right)}{(1+\Gamma)^2} < 0$$

Thus as long as there are least two firms in a industry and the exchange rates relevant for each firm are not perfectly correlated, passthrough is decreasing in $\mathit{\Gamma}$. This is the empirically relevant case since firms import from a variety of different countries with different exchange rate exposure.

How does the variance of price changes across firms vary with Γ? The variance of price changes across firms is given by taking the variance of $\Delta p_i = \frac{\alpha\Delta e + \mathit{\Gamma}\Delta p + \epsilon_i}{1+\Gamma}$.[60] We have:

[59]Here $w_i \equiv \frac{\left(\frac{s_i}{1+\Gamma}\right)}{\sum_i\left(\frac{s_i}{1+\Gamma}\right)}$, where s_i denotes the market share of firm i. By construction $\sum_i w_i = 1$. One can show that these assumptions imply that $\frac{\partial w_i}{\partial \mathit{\Gamma}} = \frac{\frac{-s_i}{(1+\Gamma)^2}\left[\sum\left(\frac{s_i}{1+\Gamma}\right) - \left(\frac{s_i}{1+\Gamma}\right)\right]}{\left(\sum\left(\frac{s_{ik}}{1+\Gamma}\right)\right)^2} < 0$, making the first term in the above expression negative as well when $0 < \theta < 1$.

[60]The specific model considered above is a special case of this expression. To see this, note that we can write the change in prices of firm i as:

$$\Delta p_i = \frac{(\alpha + \alpha\theta\mathit{\Gamma})\,\Delta e}{1+\Gamma} + \frac{\alpha(1-\theta)\mathit{\Gamma}\sum_j w_j \Delta v_j}{1+\Gamma} + \frac{\mathit{\Gamma}\sum_j w_j \epsilon_j}{1+\Gamma} + \frac{\epsilon_i}{1+\Gamma}$$

Taking the cross-sectional variance of this expression again leaves us with $Var^i(\Delta p_i) = \left(\frac{\sigma_\epsilon}{1+\Gamma}\right)^2$ because, from the perspective of firm i, the first three terms do not vary across i.

$$
\begin{aligned}
Var^i(\Delta p_i) &= Var^i\left(\frac{\alpha\Delta e}{1+\Gamma}\right) + Var^i\left(\frac{\epsilon_i}{1+\Gamma}\right) + Var^i\left(\frac{\Gamma\Delta p}{1+\Gamma}\right) \\
&\quad + Cov^i\left(\frac{\alpha\Delta e}{1+\Gamma}, \frac{\Gamma\Delta p}{1+\Gamma}\right) + Cov^i\left(\frac{\alpha\Delta e}{1+\Gamma}, \frac{\epsilon_i}{1+\Gamma}\right) + Cov^i\left(\frac{\Gamma\Delta p}{1+\Gamma}, \frac{\epsilon_i}{1+\Gamma}\right) \\
&= \left(\frac{\sigma_\epsilon}{1+\Gamma}\right)^2
\end{aligned}
$$

The first, third and fourth terms are zero because they do not vary across firms; the fifth and sixth terms are zero because WLOG the idiosyncratic shock is uncorrelated with the the exchange rate. All that is left is the second term. Clearly, $\frac{\partial var(\Delta p_i)}{\partial \Gamma} < 0$. Thus, under reasonable parameter restrictions this model implies a positive relationship between passthrough and dispersion.

B.2 Proof of Proposition from Flexible Price Section

Here we present the proof of proposition 1 from Section 3.1 that only responsiveness can that generate a positive time-series correlation between passthrough and dispersion. In particular:

Assume that α_t, Γ_t and $\sigma_{\epsilon t}$ are time-series processes that are all independent from each other. Then the time-series correlation coefficient between average exchange rate passthrough, $E^i \frac{\Delta p_{i,t}}{\Delta e_t}$, and the cross-sectional standard deviation of price changes, $Std^i\left(\Delta p_{i,t}\right)$, is given by the following expression:

$$
Corr^t\left(E^i \frac{\Delta p_{i,t}}{\Delta e_t}, Std^i\left(\Delta p_{i,t}\right)\right) = \frac{E^t\left[\alpha_t\right] E^t\left[\sigma_{\epsilon t}\right] Var^t\left(\frac{1}{1+\Gamma_t}\right)}{Std^t\left(\frac{\alpha_t}{1+\Gamma_t}\right) Std^t\left(\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right)}
$$

Proof. Our empirical moment is the time-series correlation between average exchange rate passthrough across firms and the cross-sectional standard deviation across firms. We start by computing the time-series covariance of these two objects:

$$
\begin{aligned}
&Cov^t\left(E^i \frac{\Delta p_{i,t}}{\Delta e_t}, Std^i\left(\Delta p_{i,t}\right)\right) \\
=&Cov^t\left(\frac{\alpha_t}{1+\Gamma_t}, \frac{\sigma_{nt}}{1+\Gamma_t}\right) \\
=&E^t\left[\frac{\alpha_t}{1+\Gamma_t}\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right] - E^t\left[\frac{\alpha_t}{1+\Gamma_t}\right] E^t\left[\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right].
\end{aligned}
$$

$$
\begin{aligned}
=&E^t\left[\alpha_t\right] E^t\left[\sigma_{\epsilon t}\right] E^t\left[\left(\frac{1}{1+\Gamma_t}\right)^2\right] - E^t\left[\alpha_t\right] E^t\left[\sigma_{\epsilon t}\right] E^t\left[\frac{1}{1+\Gamma_t}\right]^2 \\
=&E^t\left[\alpha_t\right] E^t\left[\sigma_{\epsilon t}\right]\left(E^t\left[\left(\frac{1}{1+\Gamma_t}\right)^2\right] - E^t\left[\frac{1}{1+\Gamma_t}\right]^2\right) \\
=&E^t\left[\alpha_t\right] E^t\left[\sigma_{\epsilon t}\right] Var^t\left(\frac{1}{1+\Gamma_t}\right) > 0.
\end{aligned}
$$

Where we have used the fact α_t, Γ_t and $\sigma_{\epsilon t}$ are independent across time to go from line 4 to line 5 and we have used the definition of variance to move from line 5 to line 6. As long as passthrough and dispersion are both positive $\left(E^t\left[\alpha_t\right]>0; E^t\left[\sigma_{\epsilon t}\right]>0\right)$, this expression can only be equal to zero is if there is no time-variation in responsiveness. That is, time-variation in responsiveness is a necessary condition for generating a positive relationship between passthrough and dispersion.

The time-series correlation between average passthrough and dispersion is just this covariance divided by their respective time-series standard deviations:

$$Corr^t\left(E^i\frac{\Delta p_{i,t}}{\Delta e_t}, Std^i\left(\Delta p_{i,t}\right)\right)=\frac{E^t\left[\alpha_t\right]E^t\left[\sigma_{\epsilon t}\right]Var^t\left(\frac{1}{1+\Gamma_t}\right)}{Std^t\left(\frac{\alpha_t}{1+\Gamma_t}\right)Std^t\left(\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right)}$$

■

B.3 More General Flexible Price Results

In this section, we show that the intuition from our simple framework in Section 3.1, survives in a more general framework that allows for general equilibrium effects. Consider the problem of a foreign firm selling goods to importers in the U.S. The firm has perfectly flexible prices that are set in dollars. The optimal flexible price of good i at the border (in logs) can be written as the sum of the gross markup (μ_i), the dollar marginal cost (mc_{it}) and an idiosyncratic shock (ϵ_i):

$$p_{it}=\mu_{it}+mc_{it}\left(e_t,\eta_{it}\right)$$

Taking the total derivative rearranging to give:

$$\Delta p_{it}=\frac{1}{1+\Gamma_t}\left[\alpha_t\Delta e_t+\Gamma_t\Delta p_t+\epsilon_{it}\right]$$

where $\Gamma_t\equiv-\frac{\partial\mu_{it}}{\partial(\Delta p_{it}-\Delta p_t)}$ is the elasticity of a firm's optimal markup with respect to its relative price, $\alpha_t\equiv\frac{\partial mc_{it}}{\partial e_t}$ is the partial elasticity of the dollar marginal cost to the exchange rate, e_t, Δp_t is the change in the aggregate price index, and $\epsilon_{it}=\Delta\eta_{it}$ is the innovation in the idiosyncratic cost shock with $\epsilon_{i,t}\sim G(0,\sigma^2_{\epsilon t})$.

In Section 3.1 we explored the case when all indirect GE effects were shut off ($\Delta p_t=0$). Here, we include them to show that most of the simple intuition about the positive relationship between MRPT and dispersion survives the introduction of GE effects. As before, we do not model the underlying primitives that give rise to variation in these three parameters and instead simply assume that these are parameters which the firm takes as exogenous. In particular, we assume that α_t, $\mathit{\Gamma}_t$ and $\sigma_{\epsilon t}$ all vary across time independently from each other but are common across all firms. Averaging across firms (across i) at a moment in time gives a simple expression for passthrough::

$$\frac{\Delta p_{it}}{\Delta e_t}=\frac{\alpha_t}{1+\Gamma_t}+\frac{\Gamma_t}{1+\Gamma_t}\frac{\Delta p_t}{\Delta e_t} \tag{10}$$

We can do some comparative statics to see how parameters affect passthrough:

$$\frac{\partial\frac{\Delta p_{it}}{\Delta e_t}}{\partial\alpha_t}=\frac{1}{1+\Gamma_t}>\ 0$$

$$\frac{\partial \frac{\Delta p_{it}}{\Delta e_t}}{\partial \Gamma_t} = -\frac{\alpha_t}{(1+\Gamma_t)^2} + \frac{1}{(1+\Gamma_t)^2}\frac{\Delta p_t}{\Delta e_t} \tag{11}$$
$$= \frac{\frac{\Delta p_t}{\Delta e_t} - \alpha_t}{(1+\Gamma_t)^2} < 0 \text{ if } \alpha_t > \frac{\Delta p_t}{\Delta e_t}$$

As before, an upper bound on the level of passthrough is given by what fraction of marginal costs are denominated in units of the foreign currency, α_t. The higher this share, the higher the potential exchange rate passthrough. General equilibrium effects operating through the domestic price level do affect the comparative static with respect to the mark-up elasticity. All things equal, if the mark-up elasticity is higher, then less of the exchange rate shock is passed into prices, which lowers $\frac{\Delta p_{it}}{\Delta e_t}$. This is the first term in equation (11). However, this is now an additional effect: a higher Γ_t means that individual prices are more sensitive to changes in the aggregate price level because strategic complementarities are higher. This is the second term in equation (11). This term is positive because $\frac{\Delta p_t}{\Delta e_t} > 0$ since increases in foreign marginal costs also raise the domestic price level. The total effect is ambiguous in general. However, for realistic cases (for instance all the parameter values we consider in our model), $\alpha_t > \frac{\Delta p_t}{\Delta e_t}$. To see this, remember that α_t is the fraction of marginal cost that is denominated in foreign currency. This gives an upper bound on the level of passthrough to individual prices from exchange rate shocks. It is hard to see how passthrough to the overall price level can be bigger than that effect since not all goods domestically are affected by the exchange rate shock and the overall-passthrough rate is affected by the level of strategic complementarities, Γ_t, which lowers the level of passthrough.

We now show that only changes in responsiveness move passthrough and price dispersion in the same direction. The variance of price changes across firms is given by:

$$var(\Delta p_i) = Var^i\left(\frac{\alpha_t \Delta e_t}{1+\Gamma_t}\right) + Var^i\left(\frac{\epsilon_{it}}{1+\Gamma_t}\right) + Var^i\left(\frac{\Gamma_t \Delta p_t}{1+\Gamma_t}\right)$$
$$+Cov^i\left(\frac{\alpha_t \Delta e_t}{1+\Gamma_t}, \frac{\Gamma_t \Delta p_t}{1+\Gamma_t}\right) + Cov^i\left(\frac{\alpha_t \Delta e_t}{1+\Gamma_t}, \frac{\epsilon_{it}}{1+\Gamma_t}\right) + Cov^i\left(\frac{\Gamma_t \Delta p_t}{1+\Gamma_t}, \frac{\epsilon_{it}}{1+\Gamma_t}\right)$$

Notice that only the second term is non-zero since it is the only term that varies across firms. Thus we have the same expression for the cross-sectional variance of firms has we had in the case when equilibrium effects were shut down. In particular, the first and third terms are zero because they are common across firms; the last terms are zero because WLOG the exchange rate innovation and the idiosyncratic cost innovation are assumed to be uncorrelated. One implication of this assumption is that the idiosyncratic shocks will also be uncorrelated with the the aggregate price level. Thus we have the our formula for the cross-sectional variance of price changes simplifies to:

$$var(\Delta p_i) = \left(\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right)^2 \tag{12}$$

Using this expression, we can do simple comparative statics to find:

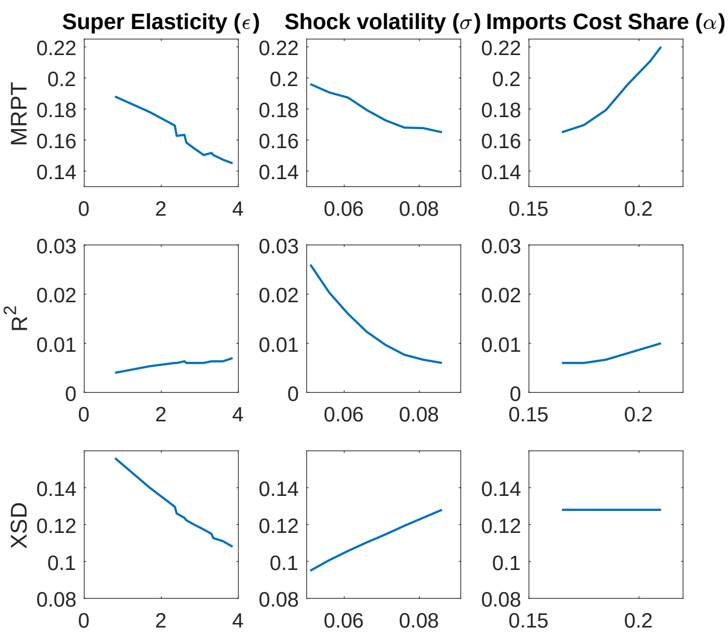
$$\frac{\partial var(\Delta p_i)}{\partial \Gamma_i} = -\frac{2\sigma_{\epsilon t}^2}{(1+\Gamma_t)^3} < 0 \tag{13}$$

In sum, even in the case when indirect GE effects are allowed, our central theoretical prediction still holds: only variation in responsiveness (Γ_t) can generate a positive time-series correlation between exchange rate passthrough and price dispersion.

B.4 Steady-State Calibration

This subsection shows how super-elasticity ε), shock volatility (σ) and import shares (α) are identified in steady-state. As described in Section 4.1.4, we jointly target average passthrough, the R^2 from our MRPT regression and the mean standard deviation of item level price changes. Figure B.4 shows that varying each parameter produces a different patterns of movement between these moments. In this exercise, we hold all parameters at their best-fit calibration and then very one parameter at a time and show its implications for MRPT, R^2 and the standard deviation of price changes. Similar patterns arise if we fix parameters at other values instead, so these relationship are quite robust.

Figure B.4: Identification of Baseline Parameters



This figure shows how our three target moments (labeled on the left-hand side) vary with parameters (labeled as the titles of each column).

B.5 Cross-Item Indirect Inference

In this section, we repeat our indirect inference exercise but now allowing for permanent firm heterogeneity instead of time-series aggregate shocks. In particular, we allow firms to differ by κ, ε and σ_A. We assume that each parameter takes on one of two values uniformly distributed around the steady-state value.[61] For example, we assume that for a particular firm, κ is either equal to $\kappa_h = .043 + \kappa_\Delta$ or $\kappa_l = .043 - \kappa_\Delta$ where κ_Δ is a parameter to be estimated which governs the degree of menu cost differences across firms. We allow for a similar two point symmetric distribution for each source of heterogeneity so that we have three parameters which must be estimated: $\theta = (\kappa_\Delta, \sigma_\Delta, \varepsilon_\Delta)$.

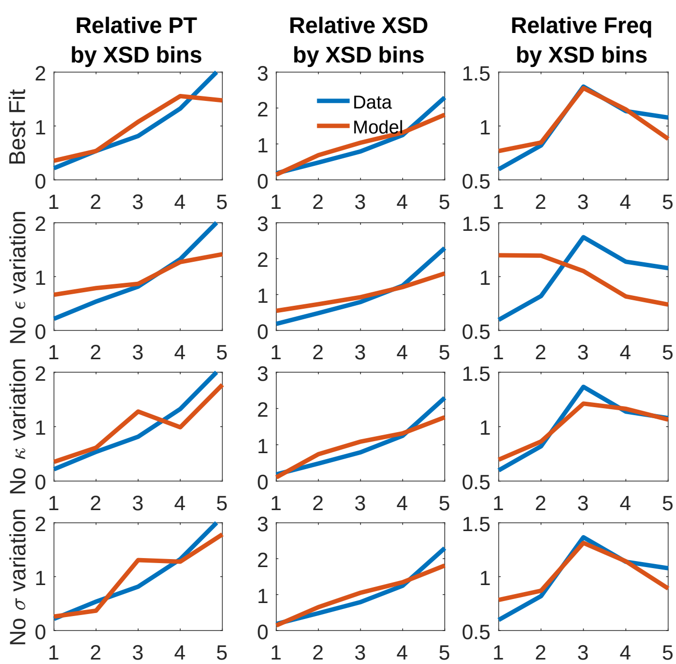
[61] When relevant, we bound the value of $\kappa_l, \varepsilon_l, \sigma_l$ at 0.

Fixing $\kappa_\Delta, \sigma_\Delta, \varepsilon_\Delta$ there are then eight different types of firms in our model (taking on high or low values for each parameter), and we assume an equal number of firms of each type.[62] After solving for the sectoral equilibrium with these eight firm types we simulate a firm panel, which we sample exactly as in the BLS microdata to account for any small sample issues which might arise in our empirical specification. From this firm panel we calculate an auxiliary model that consists of fifteen reduced form moments $g(\theta)$ which capture essential features of the data. We then try to match these simulated moments to their empirical counterparts.

To construct our empirical moments, we first sort firms into five bins by their standard deviation. We then calculate the relative standard deviation of price changes, the relative MRPT, and the relative frequency for each standard deviation bin.

Given these 15 moments, we pick our 3 parameters to solve $\widehat{\theta} = \arg\min_\theta g(\theta)' W(\theta) g(\theta)$ where $W(\theta)$ is a positive definite weight-matrix.[63] Just as in the time-series, this indirect inference estimation strongly rejects restricted specifications with no ε variation as well as specifications with any significant heterogeneity in σ. Figure B.5 displays these results visually, showing the best-fit for all fifteen moments as well as the fit of restricted models which shut down various sources of heterogeneity.

Figure B.5: Cross-Item Indirect Inference



This figure shows the model fit to all fifteen moments as well as the fit of restricted models which shut down various sources of heterogeneity.

The main take-away from this visual inspection is that the fit in the second row is dramatically worse than the fit in the first row. Turning off heterogeneity in ε means the next-best model fit does

[62] While it would be desirable to allow for more than a 2-point distribution of heterogeneity for each parameter, allowing for a 3-point distribution would require solving the model for 27 different types of firms while allowing for a 4-point distribution would require 64 firm types, so it is clear that the problem rapidly rises in difficulty. Since we want to estimate the model, we must resolve it for a large number of $\kappa_\Delta, \sigma_\Delta, \varepsilon_\Delta$ which rapidly becomes infeasible. Allowing for different numbers of each firm also greatly increases the parameter space.

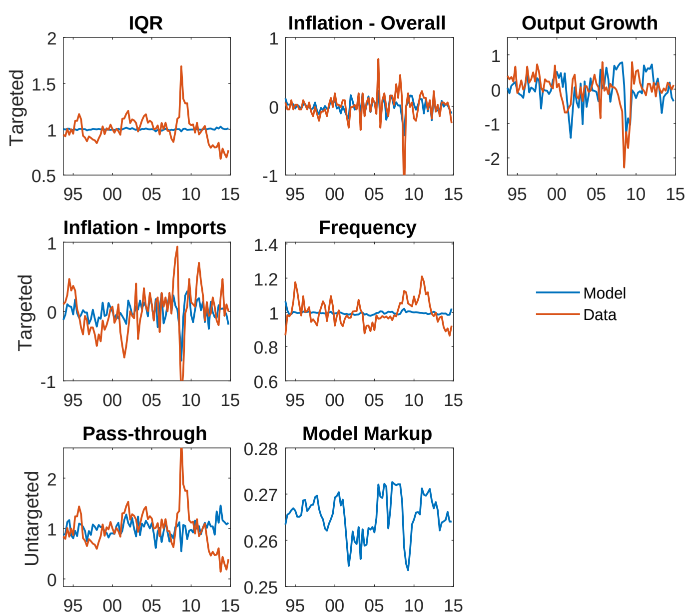
[63] We pick $W(\theta)$ to be the standard efficient weight matrix so that we can apply asymptotic formulas for standard errors but using an identity weight matrix did not change our qualitative conclusions.

not generate enough heterogeneity in price change dispersion, fails to generate enough of a positive relationship between price change dispersion and passthrough, and it implies a negative rather than positive correlation between dispersion and passthrough. In contrast, turning off heterogeneity in menu costs or in volatility has only negligible effects on the model fit.

B.6 Model Time-Series Fit with Restricted Shocks

These figures show the time-series fit of the model in section 4.4 with only responsiveness shocks or with only nominal output shocks, respectively. That is, these figures redo Figure 6 but with only a single aggregate shock instead of two shocks.

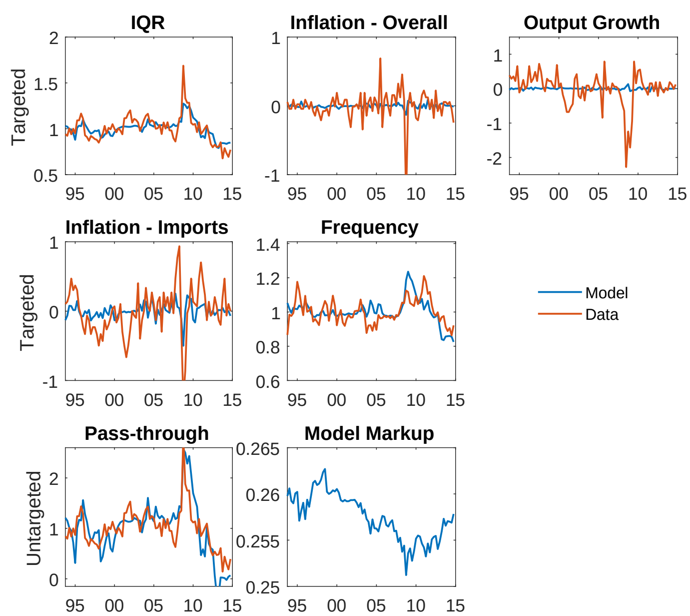
Figure B.6: Time-Series Fit of Model: No Responsiveness Shocks



Beginning from the ergodic distribution, this figure shows results when we pick exchange rates in the model to match the major currencies trade-weighted exchange rate from 1993-2015 and pick the value of the nominal shock to fit the five targeted series. Responsiveness is set equal to its steady-state value.

Clearly, the model without responsiveness shocks cannot match the behavior of IQR, frequency or passthrough and the model without nominal output shocks cannot match the joint behavior of inflation and output growth.

Figure B.7: Time-Series Fit of Model: No Nominal Output Shocks



Beginning from the ergodic distribution, this figure shows results when we pick exchange rates in the model to match the major currencies trade-weighted exchange rate from 1993-2015 and pick the value of responsiveness to fit the five targeted series. Nominal output shocks are turned off.

B.7 Additional Shocks

In addition to the above aggregate shocks, which we also explore in the cross-section, we study two additional aggregate shocks which are more applicable to the time-series. First, we allow the volatility of exchange rates to change across time, since the 2008 recession was also associated with greater exchange rate volatility. However, we find that even large increases in exchange rate volatility have only mild quantitative effects, for the same reason that changes in α have minimal affect on the dispersion of price changes.

It is also possible that the large degree of passthrough observed during the Great Recession was driven by the fact that the recession was a large shock which affected many firms. If a shock is common to more firms, then it might have greater general equilibrium effects and generate more passthrough. To assess the role of the "commonness" of shocks, we introduce time-variation in the fraction of firms that are sensitive to the exchange rate, ω. As ω rises, exchange rate shocks affect more firms and general equilibrium effects increase in importance. However, the quantitative effect of changes in ω on passthrough is relatively small and there are no effects of ω on the dispersion of price changes: increasing ω from 0.2 to 0.9 only increases passthrough from 16% to 23% and has no effect on dispersion. Thus, general equilibrium effects in our model cannot account for the empirical relationship between month-level dispersion and exchange rate passthrough.

Table A1: Alternative Business Cycle Controls

	(1) IQR+Recession Dummy	(2) IQR+GDP growth	(3) IQR+HP filtered GDP	(4) XSD+Recession Dummy	(5) XSD+GDP growth	(6) XSD+ HP filtered GDP
Δe	0.128	0.150	0.143	0.122	0.152	0.140
	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
IQR$\times\Delta$e	0.049	0.057	0.072			
	(0.010)	(0.009)	(0.010)			
IQR	-0.001	-0.002	-0.002			
	(0.001)	(0.001)	(0.001)			
XSD$\times\Delta$e				0.033	0.043	0.055
				(0.009)	(0.008)	(0.010)
XSD				-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)
Recession Dummy$\times\Delta$e	0.119			0.164		
	(0.034)			(0.033)		
Recession Dummy	-0.008			-0.009		
	(0.002)			(0.002)		
GDP Growth$\times\Delta$e		-0.028			-0.042	
		(0.010)			(0.009)	
GDP Growth		0.000			0.001	
		(0.001)			(0.001)	
HP GDP$\times\Delta$e			0.002			-0.013
			(0.011)			(0.011)
HP GDP			0.002			0.002
			(0.001)			(0.001)
Num obs	129260	129260	129260	129260	129260	129260
R^2	0.039	0.038	0.038	0.038	0.038	0.037

All regressions control for Δ cpi, Δ us gdp, Δ uscpi and allow for exchange rate passthrough to vary with business cycle controls. Monthly recession dummies picked to match NBER dates, GDP growth is real chained quarterly GDP growth and HP filtered GDP is log real GDP level Hodrick-Prescott filtered with a smoothing parameter of 1600. Regressions have country$\times$PSL fixed effects and robust standard errors clustered at the country$\times$PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A2: Time-Series Results by Country

	(1) OECD	(2) Asia	(3) Eurozone	(4) Canada	(5) Mexico
Δe	0.206	0.147	0.254	0.222	0.075
	(0.015)	(0.019)	(0.029)	(0.043)	(0.055)
IQR$\times\Delta$e	0.058	0.027	0.040	0.141	0.127
	(0.012)	(0.012)	(0.026)	(0.034)	(0.035)
IQR	-0.001	0.000	0.001	-0.004	0.002
	(0.001)	(0.001)	(0.002)	(0.026)	(0.001)
All Ctls	Yes	Yes	Yes	Yes	Yes
Num obs	68478	43590	14591	26309	8269
R^2	0.047	0.052	0.079	0.030	0.016

"All controls" are frequency of adjustment (freq), frequency of product substitutions (subs), freq and subs $\times$ Δe, gdp growth, gdp growth$\times$ Δe, SDe, SDe$\times\Delta$e, month dummies, month dummies $\times\Delta$e, t, t$\times\Delta$e, Δ cpi, Δ us gdp, Δ uscpi. See text for additional description. Regressions have country$\times$PSL fixed effects and robust standard errors clustered at the country$\times$PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A3: Results for Manufactured Goods

	(1) Overall	(2) IQR	(3) IQR+Freq	(4) IQR+All Ctrls	(5) XSD	(6) XSD+Freq	(7) XSD+All Ctrls
Δe	0.156	0.148	0.147	0.176	0.153	0.152	0.180
	(0.012)	(0.011)	(0.011)	(0.015)	(0.012)	(0.012)	(0.015)
IQR$\times\Delta$e		0.062	0.061	0.042			
		(0.010)	(0.010)	(0.010)			
IQR		-0.002	-0.002	-0.002			
		(0.001)	(0.001)	(0.001)			
XSD$\times\Delta$e					0.051	0.050	0.030
					(0.009)	(0.009)	(0.009)
XSD					-0.002	-0.002	-0.002
					(0.001)	(0.001)	(0.001)
Freq$\times\Delta$e			0.011	0.017		0.013	0.021
			(0.009)	(0.011)		(0.009)	(0.009)
Freq			0.003	0.005		0.004	0.004
			(0.001)	(0.001)		(0.001)	(0.001)
All Ctrls	No	No	No	Yes	No	No	Yes
Num obs	129260	129260	129260	129260	129260	129260	129260
R^2	0.035	0.038	0.039	0.040	0.037	0.038	0.039

"All controls" are frequency of adjustment (freq), frequency of product substitutions (subs), freq and subs $\times$ Δe, gdp growth, gdp growth$\times$ Δe, SDe, SDe$\times\Delta$e, month dummies, month dummies $\times\Delta$e, t, t$\times\Delta$e, Δ cpi, Δ us gdp, Δ uscpi. See text for additional description. Regressions have country$\times$PSL fixed effects and robust standard errors clustered at the country$\times$PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A4: Passthrough at Fixed Horizons

	(1) 1 month	(2) 3 month	(3) 6 month	(4) 12 month
Δe	0.037	0.078	0.118	0.125
	(0.006)	(0.011)	(0.017)	(0.024)
IQR×Δe	0.017	0.024	0.032	0.023
	(0.005)	(0.008)	(0.010)	(0.011)
IQR	-0.000	0.001	0.004	0.011
	(0.000)	(0.000)	(0.001)	(0.002)
All Ctrls	Yes	Yes	Yes	Yes
Num obs	354851	335848	304041	249103
R^2	0.009	0.036	0.082	0.136

These show the relationship between dispersion and passthrough without conditioning on price adjustment, at various horizons. This specification allows us to expand our sample to items with 1+ price changes instead of the 2+ in our baseline sample. See Appendix for additional description. "All controls" are frequency of adjustment (freq), frequency of product substitutions (subs), freq and subs × Δe, gdp growth, gdp growth× Δe, SDe, SDe×Δe, month dummies, month dummies ×Δe, t, t×Δe, Δ cpi, Δ us gdp, Δ uscpi. Regressions have country×PSL fixed effects and robust standard errors clustered at the country×PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A5: Cross-Item Results

	(1) XSD_{item}	(2) XSD_{item}+ $Freq_{item}$	(3) XSD_{item}+ $Freq_{item}$+IQR	(4) XSD_{item}+$Freq_{item}$ +IQR+ all controls
Δe	0.151	0.162	0.152	0.197
	(0.012)	(0.014)	(0.012)	(0.016)
$XSD_{item} \times \Delta$e	0.033	0.030	0.026	0.028
	(0.013)	(0.013)	(0.012)	(0.011)
XSD_{item}	0.001	0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
$Freq_{item} \times \Delta$e		0.024	0.025	0.041
		(0.011)	(0.010)	(0.009)
$Freq_{item}$		-0.001	-0.002	0.004
		(0.001)	(0.001)	(0.001)
IQR$\times\Delta$e			0.069	0.047
			(0.009)	(0.009)
IQR			-0.002	-0.002
			(0.001)	(0.001)
All Ctrls	No	No	No	Yes
Num obs	129260	129260	129260	129260
R^2	0.036	0.036	0.039	0.041

"All controls" are frequency of adjustment (freq), freq$\times$ Δe,frequency of product substitutions (subs), freq and subs $\times$ Δe, gdp growth, gdp growth$\times\Delta$e, SDe, SDe$\times\Delta$e, month dummies, month dummies $\times$ Δe, t, t$\times\Delta$e, Δ cpi, Δ us gdp, Δ uscpi. See text for additional description. Regressions have country$\times$PSL fixed effects and robust standard errors clustered at the country$\times$PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A6: Cross-Item Results by Country

	(1) OECD	(2) Asia	(3) Eurozone	(4) Canada	(5) Mexico
Δe	0.257	0.123	0.299	0.279	0.103
	(0.020)	(0.022)	(0.039)	(0.061)	(0.037)
$XSD_{item} \times \Delta e$	0.072	0.048	0.099	0.124	0.031
	(0.019)	(0.020)	(0.034)	(0.065)	(0.045)
XSD_{item}	0.002	-0.002	0.004	0.003	0.004
	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)
$Freq_{item} \times \Delta e$	0.085	0.012	0.067	0.178	0.076
	(0.016)	(0.014)	(0.030)	(0.055)	(0.035)
$Freq_{item}$	-0.001	-0.001	-0.004	-0.001	0.010
	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)
Num obs	68478	43590	14591	26309	8269
R^2	0.048	0.049	0.084	0.031	0.010

All regressions control for Δ cpi, Δ us gdp, Δ uscpi and have country$\times$PSL fixed effects with robust standard errors clustered at the country$\times$PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A7: Sample Summary Statistics

	Price Observations	Items	Mean Life	Mean # Changes per item	# Items w/ < 2 changes	Δp 25th percentile	Δp median	Δp75th percentile
All non-imputed	2,324,069	107,549	41.1	8.9	36385	-.03	.002	.04
Exclude comm., intrafirm, nondollar	1,188,630	58,567	34.6	5.1	22826	-.04	.005	.054
Exclude items w/ < 2 price changes	772,341	35,741	38.5	7.1	0	-.041	0.004	0.055

This table shows summary statistics for our baseline sample. Price observations is the total number of month-item price observations, items is the total number of items in the sample, mean life is the average number of months between an item's first and last observation in the data set, mean # changes per item calculates the total number of changes for each item and then averages across items, # items w/ ¡ 2 changes is just a count of the total number of items with 0 or 1 price change, and the price change percentiles show the 25th, 50th, and 75th percentile of non-zero price changes in each sample. Note that since items sometimes have missing price observations within their sample llife, the total number of price observations in column 1 is less than the number of items times the mean item life.

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Online Appendix Materials - Not For Print

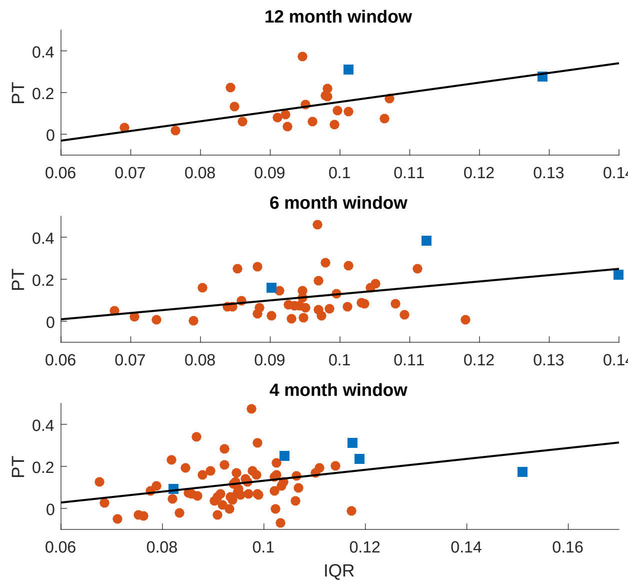
A Empirical Appendix: Online Only

A.1 Additional Empirical Results

In this section, we provide a number of robustness checks and extensions of our primary analysis.

Figure A.1 replicates Figure 2 using alternative window lengths and shows that we continue to find a strong positive relationship between our non-parametric passthrough estimates and dispersion which arises both including and excluding the Great Recession.

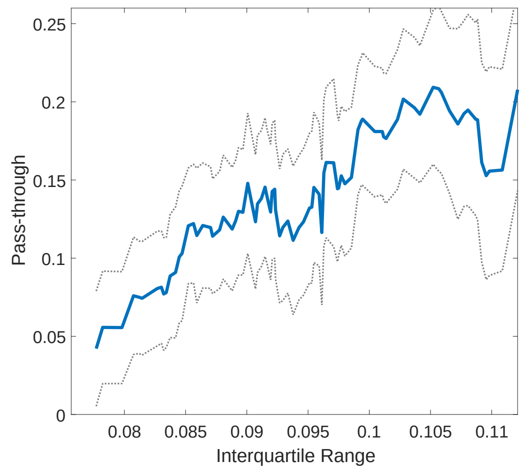
Figure A.1: Dispersion vs. passthrough: Different Windows



This figure shows the IQR of all non-zero price changes against our preferred measure of exchange rate passthrough, described below. Both statistics are computed separately in a series of disjoint windows which span our sample period. Our primary specification in the text uses 8 month windows, but this figure shows results are similar for 4, 6 and 12 month windows. Windows which have a majority of months during the Great Recession, as defined by NBER, are shown in blue. The black regression line includes all observations while the red-dotted line excludes Great Recession observations.

Figure A.2 repeats the binned time-series regression in Figure 3 using a much larger number of bins. This allows for a more non-parametric relationship between passthrough and dispersion and again shows that the linearity assumed in most of our empirical regressions is a reasonable approximation of the data. Unsurprisingly, there is somewhat more noise when performing this exercise, but the basic picture is unchanged.

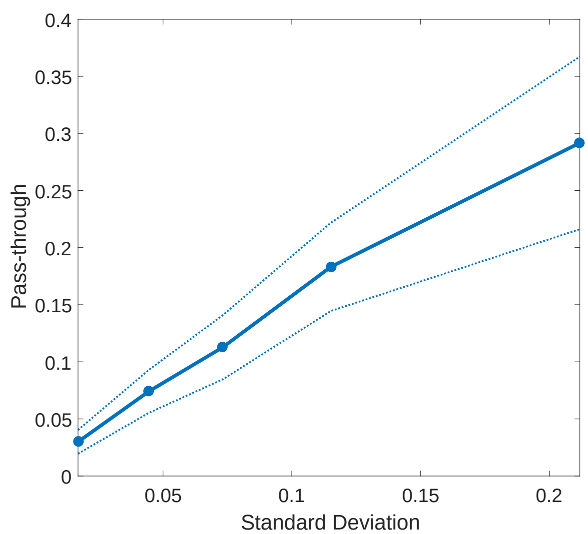
Figure A.2: Non-Parameteric IQR-passthrough Relationship



This figure shows separate estimates of regression (1) in each of 80-intervals by months' IQR. The first point includes observations from months with IQR in percentiles 1-20, the second observation months in percentiles 2-21, up to the last observation which includes observations from months in percentiles 80-100. All regressions have country × PSL fixed effects and robust standard errors are clustered at the country × PSL level. We also include controls for foreign CPI growth, US gdp growth and US CPI growth. 95% confidence intervals are shown with dotted lines, and the average IQR in each window is shown on the x-axis.

Figure A.3 repeats the binned time-series regression in Figure 3 instead using cross-item dispersion. In particular, we sort individual items by their item-level standard deviation into 5 quintiles and then run regression 1 separately in each bin. This shows that there is a positive relationship between item-level dispersion and passthrough using a specification that does not impose linearity like in Table A5.

Figure A.3: Item-Level Dispersion-passthrough Relationship



This figure shows separate estimates of regression (1) in each of 5-quintiles by the the item-level standard deviation of price changes. All regressions have country × PSL fixed effects and robust standard errors are clustered at the country × PSL level. We also include controls for foreign CPI growth, US gdp growth and US CPI growth. 95% confidence intervals are shown with dotted lines, and the average item-level standard deviation value in each quintile is shown on the x-axis.

In Table 1, Columns (4) and (7), we showed that despite the fact that dispersion is countercyclical, our patterns indeed reflect a passthrough-dispersion relationship and are not just proxying for a passthrough-business cycle relationship. In that table, we measured the business cycle using real GDP growth, but one might be concerned that real GDP growth is only a partial proxy for the business cycle. Table A1 shows that our conclusions are robust to instead measuring the business cycle using NBER Recession indicators or using HP filtered log GDP instead of gdp growth. These results show that passthrough is indeed countercyclical (at least when measuring cyclicality using real GDP growth or business cycle dates), but that this does not drive our dispersion effects. The effects of dispersion on passthrough are very similar after controlling for business cycle effects.

One might also be concerned that our results could be driven by compositional effects as the mix of product-origin countries and bilateral exchange rates varies across time. Table A2 shows that this is not the case by redoing our results restricted to particular countries/country groups.[52] These compositional concerns are more of a concern for our cross-item effects than our time-series results since an item's country of origin is necessarily fixed across time. Thus, we also repeat our cross-item results for individual countries in Table A6.

In order to use a comprehensive sample, our baseline results include a broad set of items, described in Section 2.1. However, many of these products have less product differentiation or pricing power and so are likely less well described by our theoretical price-setting model. In Table A3 we also show that our results continue to go through when using a narrower set of manufactured products that map more naturally to our model.

Finally, as an additional check of misspecification as well as the importance of our sample selection, Table A4 shows our results using an alternative passthrough specification which does not specifically condition on adjustment. More specifically, we simply regress Δp on Δe plus various additional controls and interactions over various time-intervals, without conditioning on adjustment. For example, in column 1 we simply regress the one month change in price on the one month change in exchange rates, and items in this interval may have either zero or 1 price change. In column 4 we regress one-year changes on one-year changes and item in the regressions may thus have between 0 and 11 price changes in this interval. This specification is more akin to the long-run passthrough measures in Gopinath and Itskhoki (2010). It is less useful for identification purposes but is useful for checking the robustness of our sample selection and for diagnosing misspecification. This is because it can be computed for items with a single price change, in contrast to our primary passthrough measure which can only be computed for items with at least two price changes.[53] Thus, sample sizes are expanded in this specification and we can include items with fewer price changes.

A.2 Additional Sample Summary Statistics

This section provides additional detail on the construction of our benchmark empirical sample and various related summary statistics. From our raw data which includes 2,527,619 price observations from October, 1993 – January, 2015, we begin by dropping the 203,562 price observations which are imputed and so flagged as "unusable" observations by the BLS. Row 1 of Table A7 shows the total number of price observations and items as well as various summary statistics of the raw data after dropping these unusable prices. The typical product is in the data set for a little over 3 years and changes prices roughly 9 times.

[52] There are not enough imports from individual countries aside from Mexico and Canada to get precise individual country estimates.

[53] We require at least one price change so that we can correctly measure Δe. For items with no price changes, exchange rate movements are left-censored and cannot be accurately measured. Nevertheless, despite the concerns with this measure, repeating results simply using the cumulated exchange rate change since an item enters the BLS sample allows us to further expand our sample to include all items and delivers similar results.

The last 3 columns show the 25th, median and 75th percentile of non-zero price changes. From this raw data, we then exclude commodities, intrafirm transactions and non-dollar prices in our baseline sample. We exclude non-dollar prices because these items mechanically have passthrough of 1 when not adjusting prices and so cannot be used to measure responsiveness. This means, they contain no useful information for our identification purposes. Similarly, commodities exhibit extremely high competition and are undifferentiated. This means they also exhibit nearly 100% passthrough at all times and so cannot be used to measure variation in passthrough across time. Finally, we exclude intrafirm transactions and keep only arms-length price transactions. This is because intrafirm transactions are not necessarily allocative since these transfer prices are often set for tax purposes or other internal purposes and do not necessarily have any relationship to market values so they have little value for our analysis. In total, excluding these prices, which are not informative for our analysis, reduces our sample size substantially. However, of the 1,135,439 observations dropped, the vast majority, 923,978, are intrafirm transactions. This means that although our sample size drops substantially, this is largely just from dropping prices which are essentially mismeasured relative to their allocative value. Overall, this sample selection criteria is identical to the initial sample restriction in Gopinath and Itskhoki (2010), and so makes our results more comparable to the existing literature.

Furthermore, it is important to note that our goal is not to inform aggregate statistics with our analysis. So it is not important that our sample be representative of the overall composition of import price indices. Our goal is to instead use a subset of our data to provide sharp identification, and for these purposes it makes sense to focus on the subset of data most suited for this purpose, even if it does not necessarily aggregate up to national statistics as closely as broader data sets might.

The more relevant comparison is between this initial sample cleaning and our final analysis sample, which includes only observations with at least two price changes. Comparing row 2 and 3 shows that products in our analysis sample have slightly longer average lives in the data set. This is not surprising since items which are only in the data set briefly are less likely to have measured price changes. Even less surprising, the average number of price changes per item is higher in our analysis sample, but this will mechanically be the case since this is how we are selecting our sample. However, the distribution of price changes conditional on adjustment is essentially the same. Overall these comparisons reassure us that we are not performing our analysis on a particularly unusual subset of data. Again, it is worth noting the relationship between our final sample and that in Gopinath and Itskhoki (2010). Our sample is identical to theirs except that we require items to have 2+ price changes while they require items to have only 1+ price changes because MRPT can only be measured for items with two completed price spells while their LRPT measure can be computed for items with only a single price change. However, Appendix Table A4 shows results for alternative specifications that allow us to include items with 1+ price changes. These specifications are less useful for identification purposes but are useful for checking the robustness of our sample selection and for diagnosing misspecification, and overall we find similar patterns.

B Modeling Appendix: Online Only

B.1 Interpretation of Responsiveness Fluctuations

We refer to responsiveness, Γ, as anything that affects the elasticity of a firm's desired price to a cost shock. What economic forces generate time-series variation in this responsiveness parameter? In this section, we show that many of the proposed mechanisms put forward independently to explain countercyclical dispersion, such as ambiguity aversion, customer search, employer learning and experimentation, also map into this responsiveness parameter in a way that has not previously been noted. Conversely, we show that the other dominant mechanism (other than Kimball demand) used by the international finance literature to generate incomplete passthrough – variation in market power, implies a positive relationship between passthrough and dispersion. As a result, all of these mechanisms have similar implications for the relationship between passthrough and dispersion that is at the heart of our paper.

B.1.1 Mechanisms Which Have Been Used to Explain Time-Varying Dispersion

Ambiguity Aversion

Ilut et al. (2014) show that concave hiring rules (which they microfound using an information processing framework where agents are ambiguity averse but which could result from asymmetric adjustment costs) endogenously generate higher cross-sectional (employment) dispersion and shock passthrough during recessions.

It is easy to illustrate the basic mechanism and to see how it naturally maps into responsiveness. Assume firms receive a signal s about future productivity and that the signal has an aggregate and idiosyncratic component, $s = a + \epsilon$, where the idiosyncratic shock ϵ is mean zero and i.i.d. across firms and across time. Further assume, as Ilut et al. (2014) do, that all firms follow the same decision rule, $n = f(s)$, where n is net employment growth and $f(s)$ is strictly increasing and concave. This implies that firms exhibit asymmetric adjustment to shocks: firms respond more to a signal of a given magnitude during recessions than during booms because during recessions firms are in the more concave region of their policy function. As parts 2 and 3 of Proposition 1 in Ilut et al. (2014) prove, this implies that the dispersion of employment changes is higher in recessions.

Concave policy rules also imply that aggregate employment growth is more responsive to aggregate shocks (e.g. higher cost passthrough) in recessions than booms. Formally, for any two realizations of the aggregate shocks with $a' > a$,

$$\frac{d}{da}E[n|a] > \frac{d}{da'}E[n|a'],$$

which follows directly from the strict concavity of $f(s)$. (The formal proof is given in part 1 of Proposition 1 in Ilut et al. (2014)). Thus, a positive correlation between higher dispersion and higher passthrough is a direct implication of concave policy rules.

There is a natural mapping between this mechanism and our responsiveness measure. To see this, take a first order Taylor approximation of $f(s)$ around the steady state values of a and ϵ:

$$\begin{aligned} n = f(a, \epsilon) &\approx f(\bar{a}, \bar{\epsilon}) + f_a(a - \bar{a}) + f_\epsilon(\epsilon - \bar{\epsilon}) \\ &\approx f(\bar{a}, 0) + f_a \Delta a + f_\epsilon \epsilon. \end{aligned}$$

where f_a and f_ϵ are the partial derivatives with respect to a and ϵ respectively evaluated at $\bar{a}$ and $\bar{\epsilon}$. To get from line 1 to 2 we have used the fact that the idiosyncratic shock has mean zero. Since f

is concave, these partial derivatives are positive and their magnitude governs how much the aggregate and idiosyncratic innovations affect employment growth. Comparing the above equation to our flex price equation for price changes (4), we see there is a tight connection. In particular, if we abstract from variation in alpha, there is an inverse relationship between responsiveness and the slope of $f(s)$: $1+\Gamma=\frac{\alpha}{f_a}$.

The intuition for this connection is simple: during booms, firms are in the flat region of their concave policy function where they have a low responsiveness to shocks of a given size (e.g. Γ is relatively large) . However, in recessions firms are in the steep part of their policy functions and endogenously respond more to shock of the same size (e.g. Γ is relatively small).[54] In sum, any mechanism that generates concave policy rules as a function of the firms shocks is naturally going to generate countercyclical dispersion and a positive correlation between passthrough and dispersion.

Learning

Baley and Blanco (2016) present a price-setting model with menu costs and imperfect information about idiosyncratic and aggregate productivity. They use this model analyze how price setting behavior is shaped by changes in information by analyzing the response to random increases in "uncertainty", in which firms become less informed about their underlying costs (but with no actual change in current idiosyncratic or aggregate productivity and with no changes in their volatility). That is, they study the response to a pure shock to information in which firms become less informed about their current level of productivity.

The basic logic of their model is simple to understand. Upon the arrival of a new uncertainty regime, a firm's uncertainty increases and then quickly decreases as the firm learns about the shocks they are facing. These informational shocks in turn lead to an increase in price dispersion, as proved in Baley and Blanco (2016) Proposition 6.

Is cost passthrough higher after information shocks? In order to gain intuition, it useful to examine how the level of firm's uncertainty about costs, $\varOmega_t$, affects firms incentive to learn about its markup, μ_t around a short interval of time Δ:

$$\Delta\mu_{t+\Delta}=\left(\frac{\gamma}{\varOmega_t+\gamma}\right)\mu_t+\left(\frac{\varOmega_t}{\varOmega_t+\gamma}\right)(s_{t-}s_{t-\Delta})$$

Firms update their guess of the new markup (which affects the optimal price it would like to set) as a convex combination of a weight on its previous markup and and a weight on the new information from its signals, s_t. Here γ captures the size of the information friction. It is obvious that when information is low and firms are more uncertain about their costs, they (optimally) put more weight on new information. This increases the speed of learning about the new monetary shocks hitting the economy and increases the level of passthrough. Baley and Blanco (2016) show that this implies that passthrough is higher for monetary shocks.

[54] Ilut et al. (2014) show empirically that for the U.S. manufacturing data that both employment dispersion and passthrough are higher in recessions. For passthrough, they estimate hiring rules both non-parametrically and parametrically and find higher passthrough to shocks of the same size in recessions for both rules. In particular, for the non-parametrically estimated hiring rule (see their Figure 6), the average response in boom to a 2 SD shock was +0.16% while the average response in recession to a 2 SD shock was -0.55%. These standard deviation values are calculated over the entire sample, so this shows that the response to a shock of the same size is larger in recessions. For the parametric hiring rule (see Column (I) in their Table 8), the average response in boom was +0.31% while the average response in recession was -1.05%.

The intuition is simple. The response to monetary shocks is increasing in firms' information about the size of shocks. Since we already established that a decline in information quickens the speed of learning, in the sense that agents put relatively more weight on new signals, this means that firms put more (Bayesian) weight on the new, monetary policy shock and passthrough rises. Thus, their model implies a positive relationship between price change dispersion and passthrough of cost shocks. Baley and Blanco (2016) in fact devote an entire section of their paper to showing that this mechanism is economically important in their calibrated model (see Table 4 in Section 6) and induces variation in dispersion and passthrough that lines up with the empirical facts we document in Section 2.3.

The firm learning mechanism maps precisely into our responsiveness measure: variation in responsiveness corresponds to (endogenous) variation in the speed of firm learning in response to information shocks. When firms have less information, they respond by learning more quickly about the aggregate shocks they face, increasing the responsiveness of their prices to aggregate shocks and increasing price dispersion as they respond more aggressively to idiosyncratic shocks of constant size.

Consumer Search

A growing body of research highlights the importance of changing consumer shopping behavior for business cycle outcomes. For example, Kaplan and Menzio (2016) generate business cycle fluctuations from changes in "market competitiveness". Unemployed workers spend less and search more for low prices than employed workers, so increases in unemployment increase competition. This increased competition increases incentives for firms to further reduce employment. This feedback between employment and competition can lead to self-fulfilling fluctuations and so endogenously give rise to recessions.

This mechanism is supported by a growing empirical literature. Aguiar, Hurst, and Karabarbounis (2013) document that households search more during recessions. Stroebel and Vavra (2016) show that firms adjust markups in response to changing customer price sensitivity over house price booms and busts. Munro (2016) uses UPC level panel data to show that, consistent with a changing demand elasticity story, dispersion of stores' growth rates increases during recessions and this increase is larger in markets where the increase in consumer shopping effort is highest.

Time-variation in the elasticity of demand naturally maps into our responsiveness framework. Recall, that the steady state level of responsiveness in our model is given by $\Gamma = \frac{\varepsilon}{\sigma-1}$. Thus as long as there is any adjustment of markups in response to shocks ($\varepsilon > 0$), then if certain periods of time such as recessions are characterized by increased competition (because consumers search more), with larger σ and lower markups, they will also be times of greater responsiveness and thus price change dispersion and cost passthrough.[55]

Indeed Munro (2016) explicitly explores the link between changes in the elasticity of demand (coming from variations in consumer search behavior over the cycle) and countercyclical dispersion. The intuition is straightforward: If consumers spend more time shopping for lower prices during recessions in order to smooth consumption, then firms face more elastic demand during recessions. This means that firm sales are more responsive to a given size cost shock leading to higher dispersion of firm sales and employment in recessions. Munro (2016) formalizes this mechanism in a simple business cycle model where search

[55] The presence of markup adjustment can be induced by a wide-variety of strategic-complementarities and is a pervasive assumption. In the passthrough literature this assumption is used explain incomplete passthrough and in the monetary literature it is used to explain large and persistence responses to monetary shocks.

frictions in product markets provide a role for consumer search effort to affect the elasticity of demand that firms face and shows that it generates quantitatively important fluctuations in dispersion even with no changes in the volatility of shocks.

Experimentation

Bachmann and Moscarini (2012) was one of the first papers to explore whether the increase in both macro and micro dispersion was a result of larger shocks or whether causation ran in the opposite direction. In particular, they explore whether time-varying price experimentation in response to negative aggregate shocks can explain countercyclical price dispersion dispersion in both the time-series and the cross-section of individual outcomes.

Bachmann and Moscarini (2012) start by adding imperfect information about demand to an otherwise standard monopolistically competitive model. The basic idea is that firms are heterogeneous in their elasticity of demand but face idiosyncratic demand shocks and so only gradually learn from sales about this elasticity. During booms, price dispersion is low as firms understand the demand curve they face and the cost of deviating from the average price is large in terms of lost profits. However, in recessions, when the chance of bankruptcy is high, they show that the chance that firms will choose to experiment increases because the opportunity cost of price mistakes is lower and the chance of going out of business is higher. Thus, the model delivers countercyclical price dispersion without time-varying volatility shocks.

Their model also implies that passthrough is higher when experimentation is higher. To see this, consider a recession induced by a negative TFP shock. For the firm, this decrease in TFP is a negative cost shock that increases the probability of firm exit and incentive to experiment. Bachmann and Moscarini (2012) show that in this situation the firm will choose to experiment by raising its price, and the size of the price increase is decreasing in firms expectations of future demand. The logic is simple. If the firm does not change its price, it is more likely to go out of business soon, because it likely can no longer cover its costs (this is all probabilistic, based on its beliefs about demand). In principle, it could reduce the price, hoping that true demand is so elastic that revenues will boom, however, if such a high elasticity was plausible then it would have already lowered its price during the boom when the firm was confident demand was high and it could earn large profits.[56] So the only possible move is to raise the price. This generates twin benefits as it increases the chance of survival and also provides information about the demand curve. While firms can experiment at any time, it is not profitable to do so during booms when costs are low and revenues are high and becomes profitable when costs rise in recessions. Hit by these negative cost shocks, firms then choose to experiment in the direction that at least offsets costs. In addition, more pessimistic firms raise their prices by a larger amount than firms with strong beliefs about demand (see Figure 3 in Bachmann and Moscarini (2012)). This means that pessimistic firms have higher passthrough on average than optimistic firms.

Finally, recessions lead to an increase in the mass of pessimistic firms near exit. Since pessimistic firms experiment more and have higher passthrough, this implies that both passthrough and price dispersion rise. Thus variation in the incentive to experimentation acts just like time-varying responsiveness in our baseline framework: both mechanisms generate higher price dispersion and higher passthrough during recessions.

[56]The logic is based on the envelope theorem. The first-order expected revenue gain from reducing the price cannot be large enough to more than offset the cost increase, because otherwise the previous price could not have been optimal.

B.1.2 Mechanisms Which Have Been Used to Explain Incomplete passthrough

In a recent survey of the passthrough literature (Burstein and Gopinath (2014)), they show that a number of mechanisms aside from Kimball demand map into our responsiveness parameter, $\mathit{\Gamma}$. Variation in markups arising from variation across firms' in their respective market power is the most common alternative to Kimball demand in the passthrough literature. Canonical references are Krugman (1986), Helpman and Krugman (1987), Dornbusch (1987) and more recently Atkeson and Burstein (2008). Since the body of our paper shows extensive results for Kimball demand, we focus here on this market power alternative and show that it also implies a positive correlation between passthrough and price dispersion. To be consistent with the rest of our paper, we focus on time-variation in market power though across firm variation generates similar predictions.[57]

Variation in Market Power

In this setting a discrete number of products and strategic complementarity gives rise to variable markups and markup elasticity, $\mathit{\Gamma}$, in the same form as our baseline model. The difference is that $\mathit{\Gamma}$ is determined by different parameters: variation in market power and elasticities of demand and whether there is Bertrand or Cournot competition rather than from kinked demand. Otherwise the underlying structure of the problem is the same. See Section 4.2 of Burstein and Gopinath (2014), which itself builds on Atkenson and Burstein (2008) for full details.[58] We now show that variation in Γ, coming from underlying time-variation in competititive pressure, induces a positive correlation in passthrough and price dispersion.

Despite a similar overall structure, since there are a finite number of firms and strategic complementarity, we must check whether the indirect effect of the exchange rate change coming through changes in other firms' prices overturns the basic results in Section 4. As in our baseline model, price changes depend on changes in the exchange rate, idiosyncratic shocks and changes in the overall price index:

$$\Delta p_i = \frac{\alpha \Delta e + \mathit{\Gamma} \Delta p + \epsilon_i}{1 + \Gamma}$$

Averaging across firms (across i) at a moment in time gives a simple expression for passthrough::

$$\frac{\Delta p_i}{\Delta e} = \frac{\alpha}{1+\Gamma} + \frac{\Gamma}{1+\Gamma}\frac{\Delta p}{\Delta e}$$

Next, do a comparative static with respect to Γ since this captures in a simple way how changes in market power affect passthrough:

[57] This differentiates our paper from the previous literature as it focused on variation across firms.

[58] Here we give just a flavor. Final sector output is modeled as a CES of the output of a continuum of sectors with elasticity of substitution η and sector output is CES over a finite number of differentiated products with elasticity ρ, where $1 \leq \eta \leq \rho$. They show that this implies that $\Gamma = \frac{s_i(\rho-\eta)(\rho-1)}{(\eta s_i+\rho(1-s_i))(\eta s_i+\rho(1-s_i)-1)}$ under Bertrand and $\Gamma = (\rho-1)(\frac{1}{\eta}-\frac{1}{\rho})\mu_i s_s$ under Cournot. Thus, (time) variation in Γ is induced by (time) variation in η or all market shares s_i. The latter effect would come through firm entry. One can show that in both models Γ is increasing in s_i (i.e. less competition due to less entry) and decreasing in η (higher values mean market is closer to perfect competition). Thus variation in market power can generate variation in Γ.

$$\begin{aligned}\frac{\partial \frac{\Delta p_i}{\Delta e}}{\partial \Gamma} &= -\frac{\alpha}{(1+\Gamma)^2} + \frac{1}{(1+\Gamma)^2}\frac{\Delta p}{\Delta e} \\ &= \frac{\frac{\Delta p}{\Delta e} - \alpha}{(1+\Gamma)^2} < 0 \text{ if } \alpha > \frac{\Delta p}{\Delta e}\end{aligned}$$

In general, passthrough is decreasing in Γ if general equilibrium effects are not too strong, and these effects are largely determined by the magnitude of Γ. A larger Γ means that individual prices are more sensitive to changes in the aggregate price level because strategic complementarities are stronger. As long as $\alpha > \frac{\Delta p}{\Delta e}$, the GE effect is dominated by the first term and passthrough is decreasing in Γ. This is the most relevant case since the case in which GE dominates requires passthrough to the overall price level to be bigger than the direct effect on individual prices since α is an upper bound on the direct effect.

Under the precise details of the market power model, the upper bound on the GE effect is α and under most conditions is strictly less than that. In particular, this relationship holds if firms face slightly different exchange rates. This could happen if competing firms within the same industry source inputs from different countries. Define firm $j's$ common exposure to all other firm exchange rate variation as $\Delta e_j = \theta\Delta e + (1-\theta)\Delta v_j$ with $\Delta v_j \perp \Delta e$ for all j. If $\theta = 1$ then firm j is exposed to the same exchange rate variation as all other firms and if $\theta = 0$, there is no common exchange rate variation. The most interesting case is if $0 < \theta < 1$ where there is some difference in exposure to the exchange rate between firm i and firm j. In this case we can easily show (after some patient algebra) that passthrough is decreasing in Γ just as in our baseline case as long as $0 < \theta < 1$ (and $0 < w_i < 1$ but this by construction).[59] In particular,

$$\frac{\partial\left(\frac{\Delta p_i}{\Delta e}\right)}{\partial \mathit{\Gamma}} = \frac{\alpha\left((1-\theta)(1+\mathit{\Gamma})\mathit{\Gamma}\frac{\partial w_i}{\partial \mathit{\Gamma}} + (\theta + (1-\theta)w_i - 1)\right)}{(1+\Gamma)^2} < 0$$

Thus as long as there are least two firms in a industry and the exchange rates relevant for each firm are not perfectly correlated, passthrough is decreasing in $\mathit{\Gamma}$. This is the empirically relevant case since firms import from a variety of different countries with different exchange rate exposure.

How does the variance of price changes across firms vary with Γ? The variance of price changes across firms is given by taking the variance of $\Delta p_i = \frac{\alpha\Delta e + \mathit{\Gamma}\Delta p + \epsilon_i}{1+\Gamma}$.[60] We have:

---

[59]Here $w_i \equiv \frac{\left(\frac{s_i}{1+\Gamma}\right)}{\sum_i\left(\frac{s_i}{1+\Gamma}\right)}$, where s_i denotes the market share of firm i. By construction $\sum_i w_i = 1$. One can show that these assumptions imply that $\frac{\partial w_i}{\partial \mathit{\Gamma}} = \frac{\frac{-s_i}{(1+\Gamma)^2}\left[\sum\left(\frac{s_i}{1+\Gamma}\right) - \left(\frac{s_i}{1+\Gamma}\right)\right]}{\left(\sum\left(\frac{s_{ik}}{1+\Gamma}\right)\right)^2} < 0$, making the first term in the above expression negative as well when $0 < \theta < 1$.

[60]The specific model considered above is a special case of this expression. To see this, note that we can write the change in prices of firm i as:

$$\Delta p_i = \frac{(\alpha + \alpha\theta\mathit{\Gamma})\,\Delta e}{1+\Gamma} + \frac{\alpha(1-\theta)\mathit{\Gamma}\sum_j w_j \Delta v_j}{1+\Gamma} + \frac{\mathit{\Gamma}\sum_j w_j \epsilon_j}{1+\Gamma} + \frac{\epsilon_i}{1+\Gamma}$$

Taking the cross-sectional variance of this expression again leaves us with $Var^i(\Delta p_i) = \left(\frac{\sigma_\epsilon}{1+\Gamma}\right)^2$ because, from the perspective of firm i, the first three terms do not vary across i.

$$\begin{aligned}
Var^i(\Delta p_i) &= Var^i\left(\frac{\alpha\Delta e}{1+\Gamma}\right)+Var^i\left(\frac{\epsilon_i}{1+\Gamma}\right)+Var^i\left(\frac{\Gamma\Delta p}{1+\Gamma}\right)\\
&\quad +Cov^i\left(\frac{\alpha\Delta e}{1+\Gamma},\frac{\Gamma\Delta p}{1+\Gamma}\right)+Cov^i\left(\frac{\alpha\Delta e}{1+\Gamma},\frac{\epsilon_i}{1+\Gamma}\right)+Cov^i\left(\frac{\Gamma\Delta p}{1+\Gamma},\frac{\epsilon_i}{1+\Gamma}\right)\\
&= \left(\frac{\sigma_\epsilon}{1+\Gamma}\right)^2
\end{aligned}$$

The first, third and fourth terms are zero because they do not vary across firms; the fifth and sixth terms are zero because WLOG the idiosyncratic shock is uncorrelated with the the exchange rate. All that is left is the second term. Clearly, $\frac{\partial var(\Delta p_i)}{\partial \Gamma} < 0$. Thus, under reasonable parameter restrictions this model implies a positive relationship between passthrough and dispersion.

B.2 Proof of Proposition from Flexible Price Section

Here we present the proof of proposition 1 from Section 3.1 that only responsiveness can that generate a positive time-series correlation between passthrough and dispersion. In particular:

Assume that α_t, Γ_t and $\sigma_{\epsilon t}$ are time-series processes that are all independent from each other. Then the time-series correlation coefficient between average exchange rate passthrough, $E^i\frac{\Delta p_{i,t}}{\Delta e_t}$, and the cross-sectional standard deviation of price changes, $Std^i\left(\Delta p_{i,t}\right)$, is given by the following expression:

$$Corr^t\left(E^i\frac{\Delta p_{i,t}}{\Delta e_t}, Std^i\left(\Delta p_{i,t}\right)\right)=\frac{E^t\left[\alpha_t\right]E^t\left[\sigma_{\epsilon t}\right]Var^t\left(\frac{1}{1+\Gamma_t}\right)}{Std^t\left(\frac{\alpha_t}{1+\Gamma_t}\right)Std^t\left(\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right)}$$

Proof. Our empirical moment is the time-series correlation between average exchange rate passthrough across firms and the cross-sectional standard deviation across firms. We start by computing the time-series covariance of these two objects:

$$\begin{aligned}
&Cov^t\left(E^i\frac{\Delta p_{i,t}}{\Delta e_t}, Std^i\left(\Delta p_{i,t}\right)\right)\\
=&Cov^t\left(\frac{\alpha_t}{1+\Gamma_t},\frac{\sigma_{nt}}{1+\Gamma_t}\right)\\
=&E^t\left[\frac{\alpha_t}{1+\Gamma_t}\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right]-E^t\left[\frac{\alpha_t}{1+\Gamma_t}\right]E^t\left[\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right].
\end{aligned}$$

$$\begin{aligned}
=&E^t\left[\alpha_t\right]E^t\left[\sigma_{\epsilon t}\right]E^t\left[\left(\frac{1}{1+\Gamma_t}\right)^2\right]-E^t\left[\alpha_t\right]E^t\left[\sigma_{\epsilon t}\right]E^t\left[\frac{1}{1+\Gamma_t}\right]^2\\
=&E^t\left[\alpha_t\right]E^t\left[\sigma_{\epsilon t}\right]\left(E^t\left[\left(\frac{1}{1+\Gamma_t}\right)^2\right]-E^t\left[\frac{1}{1+\Gamma_t}\right]^2\right)\\
=&E^t\left[\alpha_t\right]E^t\left[\sigma_{\epsilon t}\right]Var^t\left(\frac{1}{1+\Gamma_t}\right)>0.
\end{aligned}$$

Where we have used the fact α_t, Γ_t and $\sigma_{\epsilon t}$ are independent across time to go from line 4 to line 5 and we have used the definition of variance to move from line 5 to line 6. As long as passthrough and dispersion are both positive $\left(E^t\left[\alpha_t\right]>0; E^t\left[\sigma_{\epsilon t}\right]>0\right)$, this expression can only be equal to zero is if there is no time-variation in responsiveness. That is, time-variation in responsiveness is a necessary condition for generating a positive relationship between passthrough and dispersion.

The time-series correlation between average passthrough and dispersion is just this covariance divided by their respective time-series standard deviations:

$$Corr^t\left(E^i\frac{\Delta p_{i,t}}{\Delta e_t}, Std^i\left(\Delta p_{i,t}\right)\right)=\frac{E^t\left[\alpha_t\right]E^t\left[\sigma_{\epsilon t}\right]Var^t\left(\frac{1}{1+\Gamma_t}\right)}{Std^t\left(\frac{\alpha_t}{1+\Gamma_t}\right)Std^t\left(\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right)}$$

■

B.3 More General Flexible Price Results

In this section, we show that the intuition from our simple framework in Section 3.1, survives in a more general framework that allows for general equilibrium effects. Consider the problem of a foreign firm selling goods to importers in the U.S. The firm has perfectly flexible prices that are set in dollars. The optimal flexible price of good i at the border (in logs) can be written as the sum of the gross markup (μ_i), the dollar marginal cost (mc_{it}) and an idiosyncratic shock (ϵ_i):

$$p_{it}=\mu_{it}+mc_{it}\left(e_t,\eta_{it}\right)$$

Taking the total derivative rearranging to give:

$$\Delta p_{it}=\frac{1}{1+\Gamma_t}\left[\alpha_t\Delta e_t+\Gamma_t\Delta p_t+\epsilon_{it}\right]$$

where $\Gamma_t\equiv-\frac{\partial\mu_{it}}{\partial(\Delta p_{it}-\Delta p_t)}$ is the elasticity of a firm's optimal markup with respect to its relative price, $\alpha_t\equiv\frac{\partial mc_{it}}{\partial e_t}$ is the partial elasticity of the dollar marginal cost to the exchange rate, e_t, Δp_t is the change in the aggregate price index, and $\epsilon_{it}=\Delta\eta_{it}$ is the innovation in the idiosyncratic cost shock with $\epsilon_{i,t}\sim G(0,\sigma^2_{\epsilon t})$.

In Section 3.1 we explored the case when all indirect GE effects were shut off $(\Delta p_t=0)$. Here, we include them to show that most of the simple intuition about the positive relationship between MRPT and dispersion survives the introduction of GE effects. As before, we do not model the underlying primitives that give rise to variation in these three parameters and instead simply assume that these are parameters which the firm takes as exogenous. In particular, we assume that α_t, $\mathit{\Gamma}_t$ and $\sigma_{\epsilon t}$ all vary across time independently from each other but are common across all firms. Averaging across firms (across i) at a moment in time gives a simple expression for passthrough::

$$\frac{\Delta p_{it}}{\Delta e_t}=\frac{\alpha_t}{1+\Gamma_t}+\frac{\Gamma_t}{1+\Gamma_t}\frac{\Delta p_t}{\Delta e_t} \tag{10}$$

We can do some comparative statics to see how parameters affect passthrough:

$$\frac{\partial\frac{\Delta p_{it}}{\Delta e_t}}{\partial\alpha_t}=\frac{1}{1+\Gamma_t}>\ 0$$

$$\frac{\partial \frac{\Delta p_{it}}{\Delta e_t}}{\partial \Gamma_t} = -\frac{\alpha_t}{(1+\Gamma_t)^2} + \frac{1}{(1+\Gamma_t)^2}\frac{\Delta p_t}{\Delta e_t} = \frac{\frac{\Delta p_t}{\Delta e_t} - \alpha_t}{(1+\Gamma_t)^2} < 0 \text{ if } \alpha_t > \frac{\Delta p_t}{\Delta e_t} \tag{11}$$

As before, an upper bound on the level of passthrough is given by what fraction of marginal costs are denominated in units of the foreign currency, α_t. The higher this share, the higher the potential exchange rate passthrough. General equilibrium effects operating through the domestic price level do affect the comparative static with respect to the mark-up elasticity. All things equal, if the mark-up elasticity is higher, then less of the exchange rate shock is passed into prices, which lowers $\frac{\Delta p_{it}}{\Delta e_t}$. This is the first term in equation (11). However, this is now an additional effect: a higher Γ_t means that individual prices are more sensitive to changes in the aggregate price level because strategic complementarities are higher. This is the second term in equation (11). This term is positive because $\frac{\Delta p_t}{\Delta e_t} > 0$ since increases in foreign marginal costs also raise the domestic price level. The total effect is ambiguous in general. However, for realistic cases (for instance all the parameter values we consider in our model), $\alpha_t > \frac{\Delta p_t}{\Delta e_t}$. To see this, remember that α_t is the fraction of marginal cost that is denominated in foreign currency. This gives an upper bound on the level of passthrough to individual prices from exchange rate shocks. It is hard to see how passthrough to the overall price level can be bigger than that effect since not all goods domestically are affected by the exchange rate shock and the overall-passthrough rate is affected by the level of strategic complementarities, Γ_t, which lowers the level of passthrough.

We now show that only changes in responsiveness move passthrough and price dispersion in the same direction. The variance of price changes across firms is given by:

$$\begin{aligned} var(\Delta p_i) = {} & Var^i\left(\frac{\alpha_t \Delta e_t}{1+\Gamma_t}\right) + Var^i\left(\frac{\epsilon_{it}}{1+\Gamma_t}\right) + Var^i\left(\frac{\Gamma_t \Delta p_t}{1+\Gamma_t}\right) \\ & + Cov^i\left(\frac{\alpha_t \Delta e_t}{1+\Gamma_t}, \frac{\Gamma_t \Delta p_t}{1+\Gamma_t}\right) + Cov^i\left(\frac{\alpha_t \Delta e_t}{1+\Gamma_t}, \frac{\epsilon_{it}}{1+\Gamma_t}\right) + Cov^i\left(\frac{\Gamma_t \Delta p_t}{1+\Gamma_t}, \frac{\epsilon_{it}}{1+\Gamma_t}\right) \end{aligned}$$

Notice that only the second term is non-zero since it is the only term that varies across firms. Thus we have the same expression for the cross-sectional variance of firms has we had in the case when equilibrium effects were shut down. In particular, the first and third terms are zero because they are common across firms; the last terms are zero because WLOG the exchange rate innovation and the idiosyncratic cost innovation are assumed to be uncorrelated. One implication of this assumption is that the idiosyncratic shocks will also be uncorrelated with the the aggregate price level. Thus we have the our formula for the cross-sectional variance of price changes simplifies to:

$$var(\Delta p_i) = \left(\frac{\sigma_{\epsilon t}}{1+\Gamma_t}\right)^2 \tag{12}$$

Using this expression, we can do simple comparative statics to find:

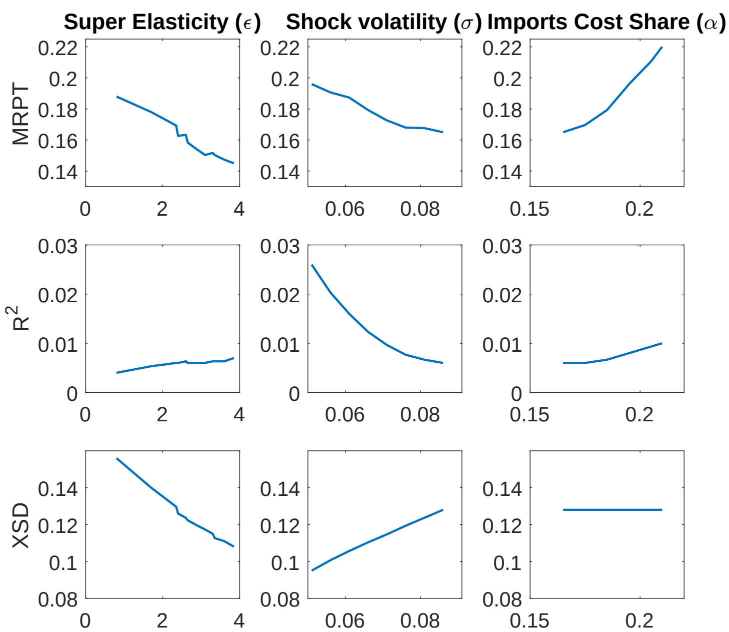
$$\frac{\partial var(\Delta p_i)}{\partial \Gamma_i} = -\frac{2\sigma_{\epsilon t}^2}{(1+\Gamma_t)^3} < 0 \tag{13}$$

In sum, even in the case when indirect GE effects are allowed, our central theoretical prediction still holds: only variation in responsiveness (Γ_t) can generate a positive time-series correlation between exchange rate passthrough and price dispersion.

B.4 Steady-State Calibration

This subsection shows how super-elasticity ε), shock volatility (σ) and import shares (α) are identified in steady-state. As described in Section 4.1.4, we jointly target average passthrough, the R^2 from our MRPT regression and the mean standard deviation of item level price changes. Figure B.4 shows that varying each parameter produces a different patterns of movement between these moments. In this exercise, we hold all parameters at their best-fit calibration and then very one parameter at a time and show its implications for MRPT, R^2 and the standard deviation of price changes. Similar patterns arise if we fix parameters at other values instead, so these relationship are quite robust.

Figure B.4: Identification of Baseline Parameters



This figure shows how our three target moments (labeled on the left-hand side) vary with parameters (labeled as the titles of each column).

B.5 Cross-Item Indirect Inference

In this section, we repeat our indirect inference exercise but now allowing for permanent firm heterogeneity instead of time-series aggregate shocks. In particular, we allow firms to differ by κ, ε and σ_A. We assume that each parameter takes on one of two values uniformly distributed around the steady-state value.[61] For example, we assume that for a particular firm, κ is either equal to $\kappa_h = .043 + \kappa_\Delta$ or $\kappa_l = .043 - \kappa_\Delta$ where κ_Δ is a parameter to be estimated which governs the degree of menu cost differences across firms. We allow for a similar two point symmetric distribution for each source of heterogeneity so that we have three parameters which must be estimated: $\theta = (\kappa_\Delta, \sigma_\Delta, \varepsilon_\Delta)$.

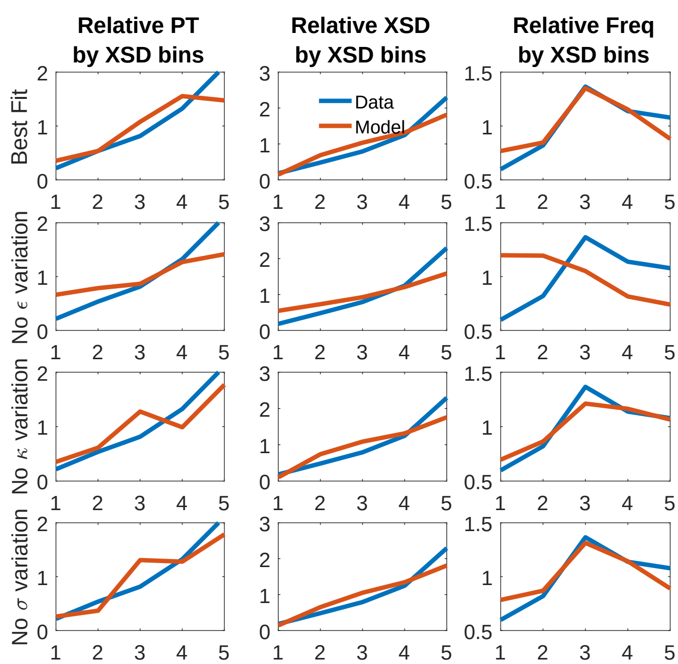
[61] When relevant, we bound the value of $\kappa_l, \varepsilon_l, \sigma_l$ at 0.

Fixing $\kappa_\Delta, \sigma_\Delta, \varepsilon_\Delta$ there are then eight different types of firms in our model (taking on high or low values for each parameter), and we assume an equal number of firms of each type.[62] After solving for the sectoral equilibrium with these eight firm types we simulate a firm panel, which we sample exactly as in the BLS microdata to account for any small sample issues which might arise in our empirical specification. From this firm panel we calculate an auxiliary model that consists of fifteen reduced form moments $g(\theta)$ which capture essential features of the data. We then try to match these simulated moments to their empirical counterparts.

To construct our empirical moments, we first sort firms into five bins by their standard deviation. We then calculate the relative standard deviation of price changes, the relative MRPT, and the relative frequency for each standard deviation bin.

Given these 15 moments, we pick our 3 parameters to solve $\widehat{\theta} = \arg\min_\theta g(\theta)' W(\theta) g(\theta)$ where $W(\theta)$ is a positive definite weight-matrix.[63] Just as in the time-series, this indirect inference estimation strongly rejects restricted specifications with no ε variation as well as specifications with any significant heterogeneity in σ. Figure B.5 displays these results visually, showing the best-fit for all fifteen moments as well as the fit of restricted models which shut down various sources of heterogeneity.

Figure B.5: Cross-Item Indirect Inference



This figure shows the model fit to all fifteen moments as well as the fit of restricted models which shut down various sources of heterogeneity.

The main take-away from this visual inspection is that the fit in the second row is dramatically worse than the fit in the first row. Turning off heterogeneity in ε means the next-best model fit does

[62] While it would be desirable to allow for more than a 2-point distribution of heterogeneity for each parameter, allowing for a 3-point distribution would require solving the model for 27 different types of firms while allowing for a 4-point distribution would require 64 firm types, so it is clear that the problem rapidly rises in difficulty. Since we want to estimate the model, we must resolve it for a large number of $\kappa_\Delta, \sigma_\Delta, \varepsilon_\Delta$ which rapidly becomes infeasible. Allowing for different numbers of each firm also greatly increases the parameter space.

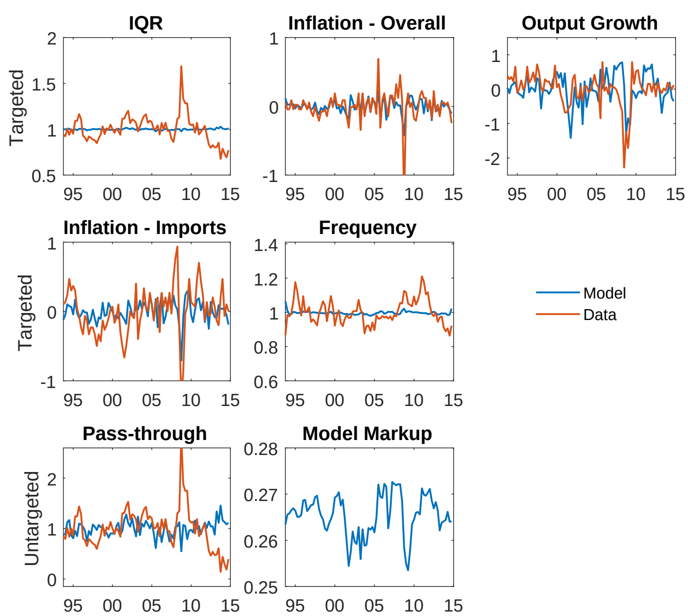
[63] We pick $W(\theta)$ to be the standard efficient weight matrix so that we can apply asymptotic formulas for standard errors but using an identity weight matrix did not change our qualitative conclusions.

not generate enough heterogeneity in price change dispersion, fails to generate enough of a positive relationship between price change dispersion and passthrough, and it implies a negative rather than positive correlation between dispersion and passthrough. In contrast, turning off heterogeneity in menu costs or in volatility has only negligible effects on the model fit.

B.6 Model Time-Series Fit with Restricted Shocks

These figures show the time-series fit of the model in section 4.4 with only responsiveness shocks or with only nominal output shocks, respectively. That is, these figures redo Figure 6 but with only a single aggregate shock instead of two shocks.

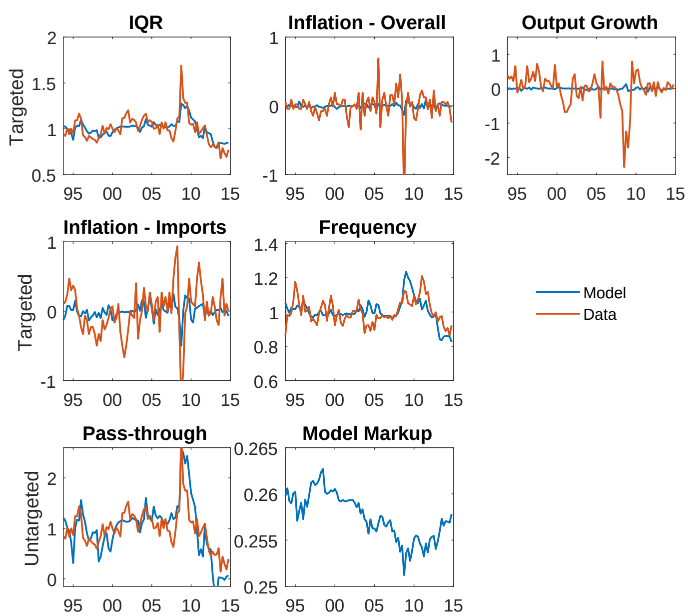
Figure B.6: Time-Series Fit of Model: No Responsiveness Shocks



Beginning from the ergodic distribution, this figure shows results when we pick exchange rates in the model to match the major currencies trade-weighted exchange rate from 1993-2015 and pick the value of the nominal shock to fit the five targeted series. Responsiveness is set equal to its steady-state value.

Clearly, the model without responsiveness shocks cannot match the behavior of IQR, frequency or passthrough and the model without nominal output shocks cannot match the joint behavior of inflation and output growth.

Figure B.7: Time-Series Fit of Model: No Nominal Output Shocks



Beginning from the ergodic distribution, this figure shows results when we pick exchange rates in the model to match the major currencies trade-weighted exchange rate from 1993-2015 and pick the value of responsiveness to fit the five targeted series. Nominal output shocks are turned off.

B.7 Additional Shocks

In addition to the above aggregate shocks, which we also explore in the cross-section, we study two additional aggregate shocks which are more applicable to the time-series. First, we allow the volatility of exchange rates to change across time, since the 2008 recession was also associated with greater exchange rate volatility. However, we find that even large increases in exchange rate volatility have only mild quantitative effects, for the same reason that changes in α have minimal affect on the dispersion of price changes.

It is also possible that the large degree of passthrough observed during the Great Recession was driven by the fact that the recession was a large shock which affected many firms. If a shock is common to more firms, then it might have greater general equilibrium effects and generate more passthrough. To assess the role of the "commonness" of shocks, we introduce time-variation in the fraction of firms that are sensitive to the exchange rate, ω. As ω rises, exchange rate shocks affect more firms and general equilibrium effects increase in importance. However, the quantitative effect of changes in ω on passthrough is relatively small and there are no effects of ω on the dispersion of price changes: increasing ω from 0.2 to 0.9 only increases passthrough from 16% to 23% and has no effect on dispersion. Thus, general equilibrium effects in our model cannot account for the empirical relationship between month-level dispersion and exchange rate passthrough.

Table A1: Alternative Business Cycle Controls

	(1) IQR+Recession Dummy	(2) IQR+GDP growth	(3) IQR+HP filtered GDP	(4) XSD+Recession Dummy	(5) XSD+GDP growth	(6) XSD+ HP filtered GDP
Δe	0.128	0.150	0.143	0.122	0.152	0.140
	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
IQR×Δe	0.049	0.057	0.072			
	(0.010)	(0.009)	(0.010)			
IQR	-0.001	-0.002	-0.002			
	(0.001)	(0.001)	(0.001)			
XSD×Δe				0.033	0.043	0.055
				(0.009)	(0.008)	(0.010)
XSD				-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)
Recession Dummy×Δe	0.119			0.164		
	(0.034)			(0.033)		
Recession Dummy	-0.008			-0.009		
	(0.002)			(0.002)		
GDP Growth×Δe		-0.028			-0.042	
		(0.010)			(0.009)	
GDP Growth		0.000			0.001	
		(0.001)			(0.001)	
HP GDP×Δe			0.002			-0.013
			(0.011)			(0.011)
HP GDP			0.002			0.002
			(0.001)			(0.001)
Num obs	129260	129260	129260	129260	129260	129260
R^2	0.039	0.038	0.038	0.038	0.038	0.037

All regressions control for Δ cpi, Δ us gdp, Δ uscpi and allow for exchange rate passthrough to vary with business cycle controls. Monthly recession dummies picked to match NBER dates, GDP growth is real chained quarterly GDP growth and HP filtered GDP is log real GDP level Hodrick-Prescott filtered with a smoothing parameter of 1600. Regressions have country×PSL fixed effects and robust standard errors clustered at the country×PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A2: Time-Series Results by Country

	(1) OECD	(2) Asia	(3) Eurozone	(4) Canada	(5) Mexico
Δe	0.206	0.147	0.254	0.222	0.075
	(0.015)	(0.019)	(0.029)	(0.043)	(0.055)
IQR$\times\Delta$e	0.058	0.027	0.040	0.141	0.127
	(0.012)	(0.012)	(0.026)	(0.034)	(0.035)
IQR	-0.001	0.000	0.001	-0.004	0.002
	(0.001)	(0.001)	(0.002)	(0.026)	(0.001)
All Ctls	Yes	Yes	Yes	Yes	Yes
Num obs	68478	43590	14591	26309	8269
R^2	0.047	0.052	0.079	0.030	0.016

"All controls" are frequency of adjustment (freq), frequency of product substitutions (subs), freq and subs $\times$ Δe, gdp growth, gdp growth$\times$ Δe, SDe, SDe$\times\Delta$e, month dummies, month dummies $\times\Delta$e, t, t$\times\Delta$e, Δ cpi, Δ us gdp, Δ uscpi. See text for additional description. Regressions have country$\times$PSL fixed effects and robust standard errors clustered at the country$\times$PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A3: Results for Manufactured Goods

	(1) Overall	(2) IQR	(3) IQR+Freq	(4) IQR+All Ctrls	(5) XSD	(6) XSD+Freq	(7) XSD+All Ctrls
Δe	0.156	0.148	0.147	0.176	0.153	0.152	0.180
	(0.012)	(0.011)	(0.011)	(0.015)	(0.012)	(0.012)	(0.015)
IQR$\times\Delta$e		0.062	0.061	0.042			
		(0.010)	(0.010)	(0.010)			
IQR		-0.002	-0.002	-0.002			
		(0.001)	(0.001)	(0.001)			
XSD$\times\Delta$e					0.051	0.050	0.030
					(0.009)	(0.009)	(0.009)
XSD					-0.002	-0.002	-0.002
					(0.001)	(0.001)	(0.001)
Freq$\times\Delta$e			0.011	0.017		0.013	0.021
			(0.009)	(0.011)		(0.009)	(0.009)
Freq			0.003	0.005		0.004	0.004
			(0.001)	(0.001)		(0.001)	(0.001)
All Ctrls	No	No	No	Yes	No	No	Yes
Num obs	129260	129260	129260	129260	129260	129260	129260
R^2	0.035	0.038	0.039	0.040	0.037	0.038	0.039

"All controls" are frequency of adjustment (freq), frequency of product substitutions (subs), freq and subs $\times$ Δe, gdp growth, gdp growth$\times$ Δe, SDe, SDe$\times\Delta$e, month dummies, month dummies $\times\Delta$e, t, t$\times\Delta$e, Δ cpi, Δ us gdp, Δ uscpi. See text for additional description. Regressions have country$\times$PSL fixed effects and robust standard errors clustered at the country$\times$PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A4: Passthrough at Fixed Horizons

	(1) 1 month	(2) 3 month	(3) 6 month	(4) 12 month
Δe	0.037	0.078	0.118	0.125
	(0.006)	(0.011)	(0.017)	(0.024)
IQR$\times\Delta$e	0.017	0.024	0.032	0.023
	(0.005)	(0.008)	(0.010)	(0.011)
IQR	-0.000	0.001	0.004	0.011
	(0.000)	(0.000)	(0.001)	(0.002)
All Ctrls	Yes	Yes	Yes	Yes
Num obs	354851	335848	304041	249103
R^2	0.009	0.036	0.082	0.136

These show the relationship between dispersion and passthrough without conditioning on price adjustment, at various horizons. This specification allows us to expand our sample to items with 1+ price changes instead of the 2+ in our baseline sample. See Appendix for additional description. "All controls" are frequency of adjustment (freq), frequency of product substitutions (subs), freq and subs $\times$ Δe, gdp growth, gdp growth$\times$ Δe, SDe, SDe$\times\Delta$e, month dummies, month dummies $\times\Delta$e, t, t$\times\Delta$e, Δ cpi, Δ us gdp, Δ uscpi. Regressions have country$\times$PSL fixed effects and robust standard errors clustered at the country$\times$PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A5: Cross-Item Results

	(1) XSD_{item}	(2) XSD_{item}+ $Freq_{item}$	(3) XSD_{item}+ $Freq_{item}$+IQR	(4) XSD_{item}+$Freq_{item}$ +IQR+ all controls
Δe	0.151	0.162	0.152	0.197
	(0.012)	(0.014)	(0.012)	(0.016)
$XSD_{item} \times \Delta$e	0.033	0.030	0.026	0.028
	(0.013)	(0.013)	(0.012)	(0.011)
XSD_{item}	0.001	0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
$Freq_{item} \times \Delta$e		0.024	0.025	0.041
		(0.011)	(0.010)	(0.009)
$Freq_{item}$		-0.001	-0.002	0.004
		(0.001)	(0.001)	(0.001)
IQR$\times \Delta$e			0.069	0.047
			(0.009)	(0.009)
IQR			-0.002	-0.002
			(0.001)	(0.001)
All Ctrls	No	No	No	Yes
Num obs	129260	129260	129260	129260
R^2	0.036	0.036	0.039	0.041

"All controls" are frequency of adjustment (freq), freq$\times$ Δe,frequency of product substitutions (subs), freq and subs $\times$ Δe, gdp growth, gdp growth$\times\Delta$e, SDe, SDe$\times\Delta$e, month dummies, month dummies $\times$ Δe, t, t$\times\Delta$e, Δ cpi, Δ us gdp, Δ uscpi. See text for additional description. Regressions have country$\times$PSL fixed effects and robust standard errors clustered at the country$\times$PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A6: Cross-Item Results by Country

	(1) OECD	(2) Asia	(3) Eurozone	(4) Canada	(5) Mexico
Δe	0.257	0.123	0.299	0.279	0.103
	(0.020)	(0.022)	(0.039)	(0.061)	(0.037)
$XSD_{item} \times \Delta e$	0.072	0.048	0.099	0.124	0.031
	(0.019)	(0.020)	(0.034)	(0.065)	(0.045)
XSD_{item}	0.002	-0.002	0.004	0.003	0.004
	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)
$Freq_{item} \times \Delta e$	0.085	0.012	0.067	0.178	0.076
	(0.016)	(0.014)	(0.030)	(0.055)	(0.035)
$Freq_{item}$	-0.001	-0.001	-0.004	-0.001	0.010
	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)
Num obs	68478	43590	14591	26309	8269
R^2	0.048	0.049	0.084	0.031	0.010

All regressions control for Δ cpi, Δ us gdp, Δ uscpi and have country$\times$PSL fixed effects with robust standard errors clustered at the country$\times$PSL level. Dispersion and frequency are standardized so that coefficients represent a one-standard deviation effect. Sample period is October 1993-January 2015.

Table A7: Sample Summary Statistics

	Price Observations	Items	Mean Life	Mean # Changes per item	# Items w/ < 2 changes	Δp 25th percentile	Δp median	Δp75th percentile
All non-imputed	2,324,069	107,549	41.1	8.9	36385	-.03	.002	.04
Exclude comm., intrafirm, nondollar	1,188,630	58,567	34.6	5.1	22826	-.04	.005	.054
Exclude items w/ < 2 price changes	772,341	35,741	38.5	7.1	0	-.041	0.004	0.055

This table shows summary statistics for our baseline sample. Price observations is the total number of month-item price observations, items is the total number of items in the sample, mean life is the average number of months between an item's first and last observation in the data set, mean # changes per item calculates the total number of changes for each item and then averages across items, # items w/ ¡ 2 changes is just a count of the total number of items with 0 or 1 price change, and the price change percentiles show the 25th, 50th, and 75th percentile of non-zero price changes in each sample. Note that since items sometimes have missing price observations within their sample llife, the total number of price observations in column 1 is less than the number of items times the mean item life.

Table 5: Parameter Values

Parameter	Symbol	Menu Cost Model	Source
Discount factor	β	$0.96^{1/12}$	Annualized interest rate of 4%
Fraction of imports	$\omega/(1+\omega)$	14.5%	BEA input-output table
Cost sensitivity to ER shock			
Foreign firms	α	0.165	Estimation (see text)
U.S. firms	α^{US}	0	
Menu cost	κ	5.0%	Estimation (see text)
Markup elasticity	ε	2.35	Estimation (see text)
Demand elasticity	σ	5	Broda and Weinstein (2006)
Std. dev. exchange rate shock, e_t	σ_e	2.5%	Match bilateral RER
Idiosyncratic productivity process, a_t			
Std. dev. of shock	σ_A	8.6%	Estimation (see text)
Persistence of shock	ρ_A	0.85	Gopinath and Itshkoki (2010)

Table 6: Estimated Parameters and Fit

Parameter	Estimate	95% Confidence Interval
σ_ε	0.365	(0.347,0.383)
σ_σ	0.000	(0.00,.0053)
σ_κ	0.014	(0.00,.0337)
ρ	0.845	(0.838,0.852)

Models	Wald-Statistic/Likelihood Ratio	95% Critical Value	99% Critical Value
Unrestricted Model	41.64	19.68	24.72
$\sigma_\varepsilon = 0$	113.2851	3.84	6.64

Asymptotic s.e.'s for parameters in parantheses. Unrestricted model Wald-Statistic: $g\left(\widehat{\theta}\right)' W\left(\widehat{\theta}\right)' g\left(\widehat{\theta}\right) \sim \chi^2(11)$

Restricted models: $2\left[g\left(\widehat{\theta}_r\right)' W\left(\widehat{\theta}_u\right)' g\left(\widehat{\theta}_r\right) - g\left(\widehat{\theta}_r\right)' W\left(\widehat{\theta}_u\right)' g\left(\widehat{\theta}_r\right)\right] \sim \chi^2(1)$

Table Doc File

Table 1

	(1) Overall	(2) IQR	(3) IQR+Freq	(4) IQR+All Ctrls	(5) XSD	(6) XSD+Freq	(7) XSD+All Ctrls
Δe	0.154	0.143	0.143	0.174	0.141	0.141	0.176
	(0.012)	(0.011)	(0.011)	(0.015)	(0.012)	(0.012)	(0.015)
IQR×Δe		0.070	0.070	0.050			
		(0.009)	(0.009)	(0.009)			
IQR		-0.002	-0.002	-0.002			
		(0.001)	(0.001)	(0.001)			
XSD×Δe					0.058	0.058	0.038
					(0.009)	(0.009)	(0.009)
XSD					-0.002	-0.002	-0.002
					(0.001)	(0.001)	(0.001)
Freq×Δe			0.010	0.019		0.012	
			(0.009)	(0.009)		(0.009)	
Freq			0.004	0.004		0.004	
			(0.001)	(0.001)		(0.001)	
All Ctrls	No	No	No	Yes	No	No	Yes
Num obs	129260	129260	129260	129260	129260	129260	129260
R^2	0.035	0.038	0.039	0.040	0.037	0.038	0.039

Table 2

	(1) Overall	(2) IQR	(3) IQR+Freq	(4) IQR+All Ctrls	(5) XSD	(6) XSD+Freq	(7) XSD+All Ctrls
Δe	0.129	0.131	0.132	0.159	0.128	0.129	0.160
	(0.012)	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)	(0.014)
IQR×Δe		0.037	0.038	0.027			
		(0.011)	(0.011)	(0.012)			
IQR		0.003	0.004	0.004			
		(0.001)	(0.001)	(0.001)			
XSD×Δe					0.015	0.016	0.009
					(0.009)	(0.009)	(0.009)
XSD					0.003	0.003	0.003
					(0.001)	(0.001)	(0.001)
Freq×Δe			0.014	0.024		0.013	0.024
			(0.009)	(0.010)		(0.009)	(0.010)
Freq			0.004	0.004		0.004	0.004
			(0.001)	(0.001)		(0.001)	(0.001)
All Ctrls	No	No	No	Yes	No	No	Yes
Num obs	119816	119816	119816	119816	119816	119816	119816
R^2	0.034	0.035	0.036	0.037	0.035	0.036	0.037

Table 3

	(1) IQR_{sector}	(2) IQR_{sector}+ $IQR_{overall}$	(3) IQR_{abs_dev}	(4) $IQR_{\%\_dev}$	(5) IQR_{sector}+ Month dummy×Δe
Δe	0.184	0.174	0.193	0.187	-0.050
	(0.015)	(0.015)	(0.014)	(0.015)	(0.104)
IQR_{sector} × Δe	0.038	0.025			0.024
	(0.011)	(0.011)			(0.011)
IQR_{sector}	-0.003	-0.002			-0.001
	(0.001)	(0.001)			(0.001)
$IQR_{overall}$ × Δe		0.040			
		(0.009)			
$IQR_{overall}$		-0.001			
		(0.001)			
IQR_{abs_dev} × Δe			0.026		
			(0.011)		
IQR_{abs_dev}			-0.001		
			(0.001)		
$IQR_{\%\_dev}$ × Δe				0.030	
				(0.012)	
$IQR_{\%\_dev}$				-0.001	
				(0.001)	
Month Dummy	No	No	No	No	Yes
Month Dummy×Δe	No	No	No	No	Yes
All Ctrls	Yes	Yes	Yes	Yes	Yes
Num obs	129232	129232	129232	129232	129232
R^2	0.040	0.040	0.039	0.039	0.067

Table 4

	(1) Full Inter-action	(2) IQR+ IQR^2	(3) Δe+ Δe^2	(4) Δe+ l. Δe	(5) Δe+ l. Δe+ l2. Δe	(6) Δe>0	(7) Δe<0	(8) 5+chgs	(9) <=5 chgs	(10) Median Regs
Δe	0.158 (0.014)	0.164 (0.015)	0.188 (0.015)	0.239 (0.035)	0.265 (0.039)	0.168 (0.020)	0.178 (0.018)	0.199 (0.017)	0.098 (0.014)	0.163 (0.010)
IQR ×Δe	0.026 (0.009)	0.032 (0.011)	0.066 (0.012)	0.076 (0.022)	0.073 (0.026)	0.054 (0.014)	0.037 (0.014)	0.060 (0.011)	0.024 (0.013)	0.029 (0.006)
IQR	0.001 (0.001)	0.001 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.004 (0.001)	-0.000 (0.001)	-0.003 (0.001)	0.003 (0.001)	0.003 (0.001)
IQR^2×Δe		-0.004 (0.005)								
IQR^2	-0.004 (0.000)	-0.005 (0.000)								
IQR×$(\Delta e)^2$			0.057 (0.022)							
$(\Delta e)^2$	-0.012 (0.022)		0.059 (0.023)							
IQR×l.Δe				0.070 (0.019)	0.074 (0.030)					
l.Δe				0.065 (0.014)	0.086 (0.027)					
IQR×l2.Δe					0.032 (0.025)					
l2.Δe					0.063 (0.018)					
All Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num obs	129260	129260	129260	57589	42127	62551	62297	114141	28014	129260
R^2	0.044	0.044	0.041	0.025	0.028	0.049	0.057	0.029	0.095	

Table A1

	(1) IQR+Recession Dummy	(2) IQR+GDP growth	(3) IQR+HP filtered GDP	(4) XSD+Recession Dummy	(5) XSD+GDP growth	(6) XSD+ HP filtered GDP
Δe	0.128	0.150	0.143	0.122	0.152	0.140
	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
IQR×Δe	0.049	0.057	0.072			
	(0.010)	(0.009)	(0.010)			
IQR	-0.001	-0.002	-0.002			
	(0.001)	(0.001)	(0.001)			
XSD×Δe				0.033	0.043	0.055
				(0.009)	(0.008)	(0.010)
XSD				-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)
Recession Dummy×Δe	0.119			0.164		
	(0.034)			(0.033)		
Recession Dummy	-0.008			-0.009		
	(0.002)			(0.002)		
GDP Growth×Δe		-0.028			-0.042	
		(0.010)			(0.009)	
GDP Growth		0.000			0.001	
		(0.001)			(0.001)	
HP GDP×Δe			0.002			-0.013
			(0.011)			(0.011)
HP GDP			0.002			0.002
			(0.001)			(0.001)
Num obs	129260	129260	129260	129260	129260	129260
R^2	0.039	0.038	0.038	0.038	0.038	0.037

Table A2

	(1) OECD	(2) Asia	(3) Eurozone	(4) Canada	(5) Mexico
Δe	0.206	0.147	0.254	0.222	0.075
	(0.015)	(0.019)	(0.029)	(0.043)	(0.055)
IQR×Δe	0.058	0.027	0.040	0.141	0.127
	(0.012)	(0.012)	(0.026)	(0.034)	(0.035)
IQR	-0.001	0.000	0.001	-0.004	0.002
	(0.001)	(0.001)	(0.002)	(0.026)	(0.001)
All Ctls	Yes	Yes	Yes	Yes	Yes
Num obs	68478	43590	14591	26309	8269
R^2	0.047	0.052	0.079	0.030	0.016

Table A3

	(1) Overall	(2) IQR	(3) IQR+Freq	(4) IQR+All Ctrls	(5) XSD	(6) XSD+Freq	(7) XSD+All Ctrls
Δe	0.156	0.148	0.147	0.176	0.153	0.152	0.180
	(0.012)	(0.011)	(0.011)	(0.015)	(0.012)	(0.012)	(0.015)
IQR×Δe		0.062	0.061	0.042			
		(0.010)	(0.010)	(0.010)			
IQR		-0.002	-0.002	-0.002			
		(0.001)	(0.001)	(0.001)			
XSD×Δe					0.051	0.050	0.030
					(0.009)	(0.009)	(0.009)
XSD					-0.002	-0.002	-0.002
					(0.001)	(0.001)	(0.001)
Freq×Δe			0.011	0.017		0.013	0.021
			(0.009)	(0.011)		(0.009)	(0.009)
Freq			0.003	0.005		0.004	0.004
			(0.001)	(0.001)		(0.001)	(0.001)
All Ctrls	No	No	No	Yes	No	No	Yes
Num obs	129260	129260	129260	129260	129260	129260	129260
R^2	0.035	0.038	0.039	0.040	0.037	0.038	0.039

Table A4

	(1) 1 month	(2) 3 month	(3) 6 month	(4) 12 month
Δe	0.037	0.078	0.118	0.125
	(0.006)	(0.011)	(0.017)	(0.024)
IQR×Δe	0.017	0.024	0.032	0.023
	(0.005)	(0.008)	(0.010)	(0.011)
IQR	-0.000	0.001	0.004	0.011
	(0.000)	(0.000)	(0.001)	(0.002)
All Ctrls	Yes	Yes	Yes	Yes
Num obs	354851	335848	304041	249103
R^2	0.009	0.036	0.082	0.136

Table A5

	(1) XSD_{item}	(2) XSD_{item}+ $Freq_{item}$	(3) XSD_{item}+ $Freq_{item}$+IQR	(4) XSD_{item}+$Freq_{item}$ +IQR+ all controls
Δe	0.151	0.162	0.152	0.197
	(0.012)	(0.014)	(0.012)	(0.016)
XSD_{item}×Δe	0.033	0.030	0.026	0.028
	(0.013)	(0.013)	(0.012)	(0.011)
XSD_{item}	0.001	0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
$Freq_{item}$×Δe		0.024	0.025	0.041
		(0.011)	(0.010)	(0.009)
$Freq_{item}$		-0.001	-0.002	0.004
		(0.001)	(0.001)	(0.001)
IQR×Δe			0.069	0.047
			(0.009)	(0.009)
IQR			-0.002	-0.002
			(0.001)	(0.001)
All Ctrls	No	No	No	Yes
Num obs	129260	129260	129260	129260
R^2	0.036	0.036	0.039	0.041

Table A6

	(1) OECD	(2) Asia	(3) Eurozone	(4) Canada	(5) Mexico
Δe	0.257	0.123	0.299	0.279	0.103
	(0.020)	(0.022)	(0.039)	(0.061)	(0.037)
$XSD_{item} \times \Delta e$	0.072	0.048	0.099	0.124	0.031
	(0.019)	(0.020)	(0.034)	(0.065)	(0.045)
XSD_{item}	0.002	-0.002	0.004	0.003	0.004
	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)
$Freq_{item} \times \Delta e$	0.085	0.012	0.067	0.178	0.076
	(0.016)	(0.014)	(0.030)	(0.055)	(0.035)
$Freq_{item}$	-0.001	-0.001	-0.004	-0.001	0.010
	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)
Num obs	68478	43590	14591	26309	8269
R^2	0.048	0.049	0.084	0.031	0.010

Table A7

	Price Observations	Items	Mean Life	Mean # Changes per item	# Items w/ < 2 changes	Δp 25th percentile	Δp median	Δp75th percentile
All non-imputed	2,324,069	107,549	41.1	8.9	36385	-.03	.002	.04
Exclude comm., intrafirm, nondollar	1,188,630	58,567	34.6	5.1	22826	-.04	.005	.054
Exclude items w/ < 2 price changes	772,341	35,741	38.5	7.1	0	-.041	0.004	0.055

Table 6: Estimated Parameters and Fit

Parameter	Estimate	95% Confidence Interval
σ_ε	0.365	(0.347,0.383)
σ_σ	0.000	(0.00,.0053)
σ_κ	0.014	(0.00,.0337)
ρ	0.845	(0.838,0.852)

Models	Wald-Statistic/Likelihood Ratio	95% Critical Value	99% Critical Value
Unrestricted Model	41.64	19.68	24.72
$\sigma_\varepsilon = 0$	113.2851	3.84	6.64

Asymptotic s.e.'s for parameters in parantheses. Unrestricted model Wald-Statistic: $g\left(\widehat{\theta}\right)' W\left(\widehat{\theta}\right)' g\left(\widehat{\theta}\right) \sim \chi^2(11)$

Restricted models: $2\left[g\left(\widehat{\theta}_r\right)' W\left(\widehat{\theta}_u\right)' g\left(\widehat{\theta}_r\right) - g\left(\widehat{\theta}_r\right)' W\left(\widehat{\theta}_u\right)' g\left(\widehat{\theta}_r\right)\right] \sim \chi^2(1)$

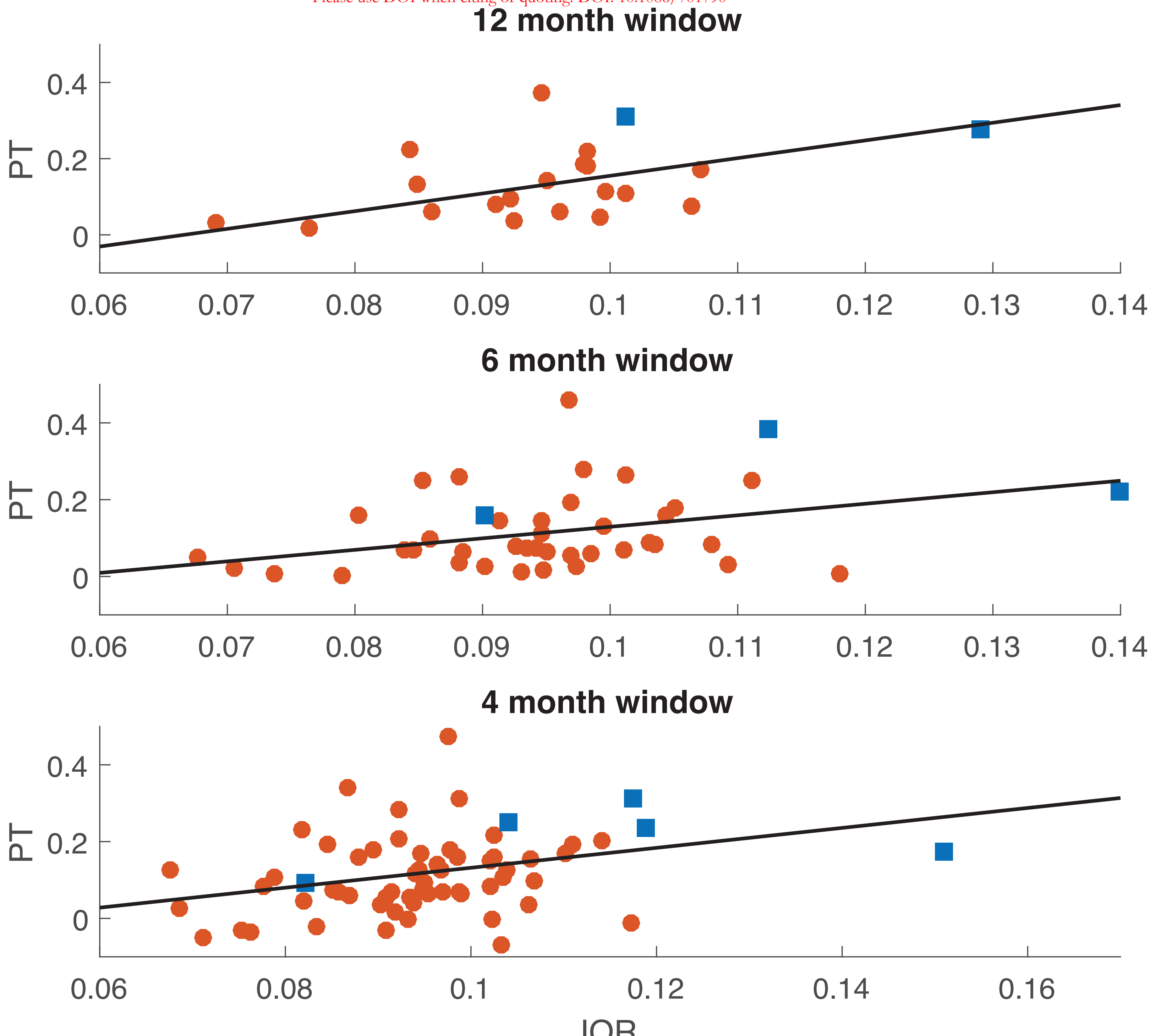
Table A6

	(1) OECD	(2) Asia	(3) Eurozone	(4) Canada	(5) Mexico
Δe	0.257	0.123	0.299	0.279	0.103
	(0.020)	(0.022)	(0.039)	(0.061)	(0.037)
$XSD_{item} \times \Delta e$	0.072	0.048	0.099	0.124	0.031
	(0.019)	(0.020)	(0.034)	(0.065)	(0.045)
XSD_{item}	0.002	-0.002	0.004	0.003	0.004
	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)
$Freq_{item} \times \Delta e$	0.085	0.012	0.067	0.178	0.076
	(0.016)	(0.014)	(0.030)	(0.055)	(0.035)
$Freq_{item}$	-0.001	-0.001	-0.004	-0.001	0.010
	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)
Num obs	68478	43590	14591	26309	8269
R^2	0.048	0.049	0.084	0.031	0.010

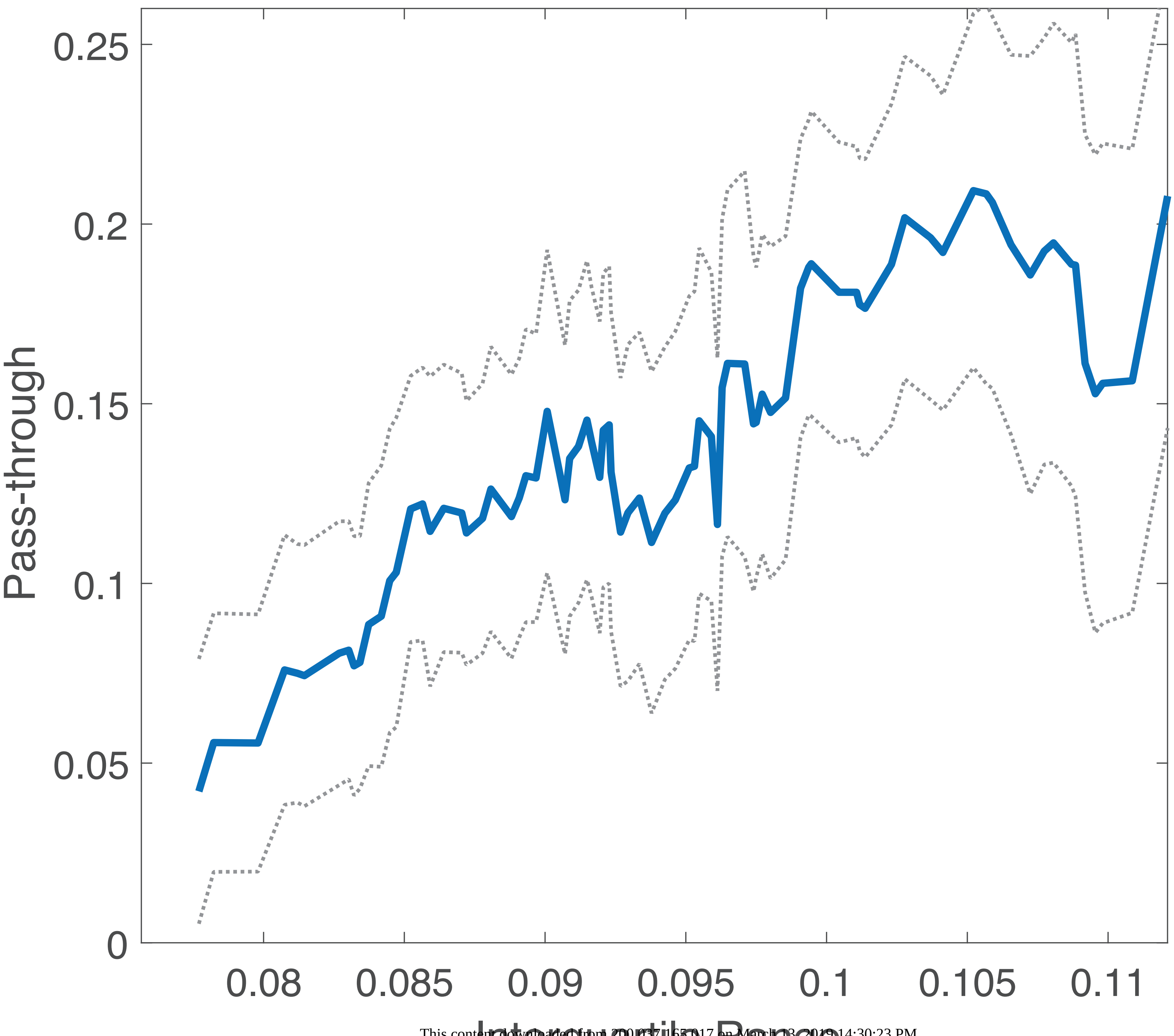
Table A7

	Price Observations	Items	Mean Life	Mean # Changes per item	# Items w/ < 2 changes	Δp 25th percentile	Δp median	Δp75th percentile
All non-imputed	2,324,069	107,549	41.1	8.9	36385	-.03	.002	.04
Exclude comm., intrafirm, nondollar	1,188,630	58,567	34.6	5.1	22826	-.04	.005	.054
Exclude items w/ < 2 price changes	772,341	35,741	38.5	7.1	0	-.041	0.004	0.055

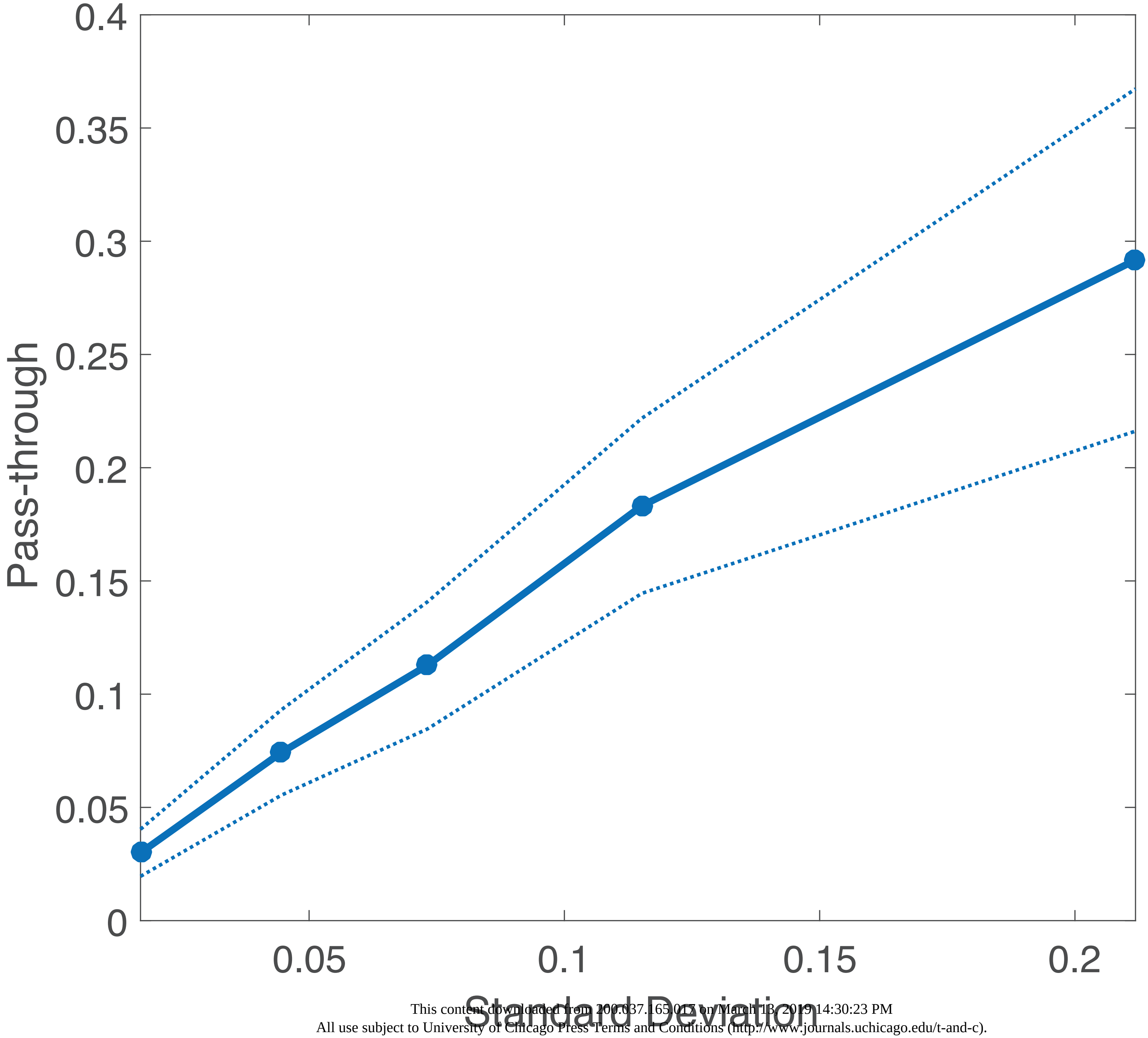
appendix fig 1



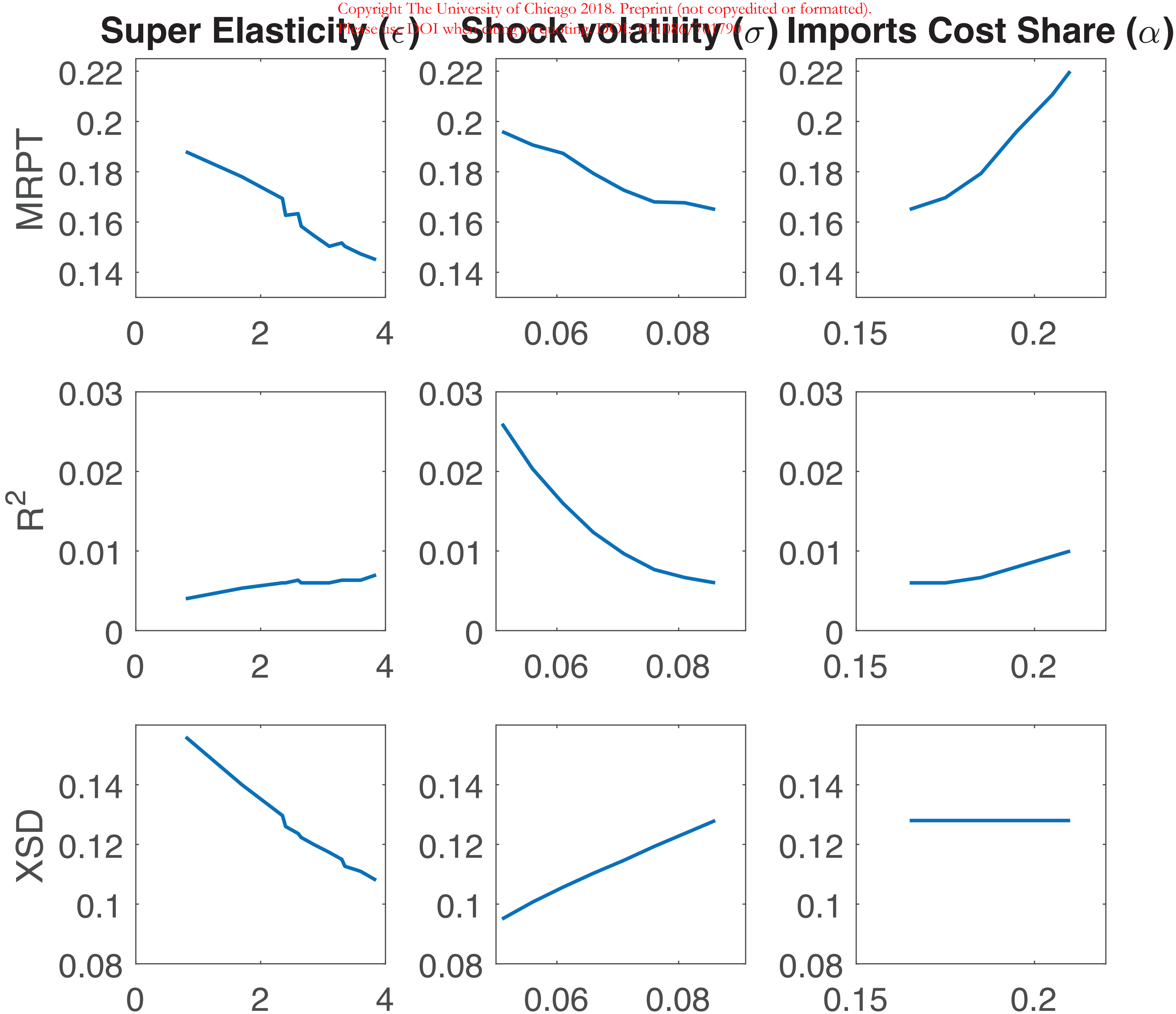
appendix fig 2



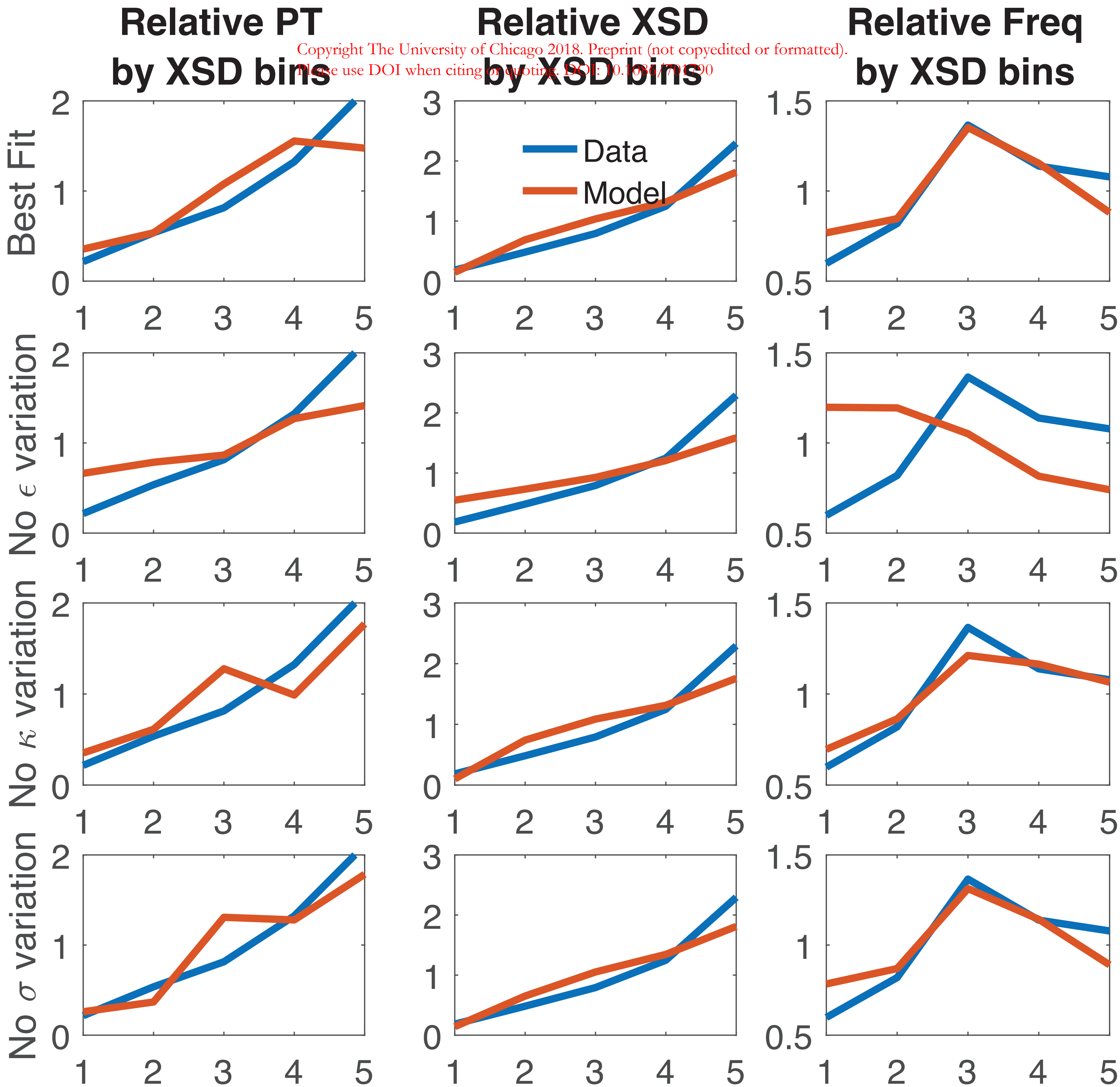
appendix fig 3



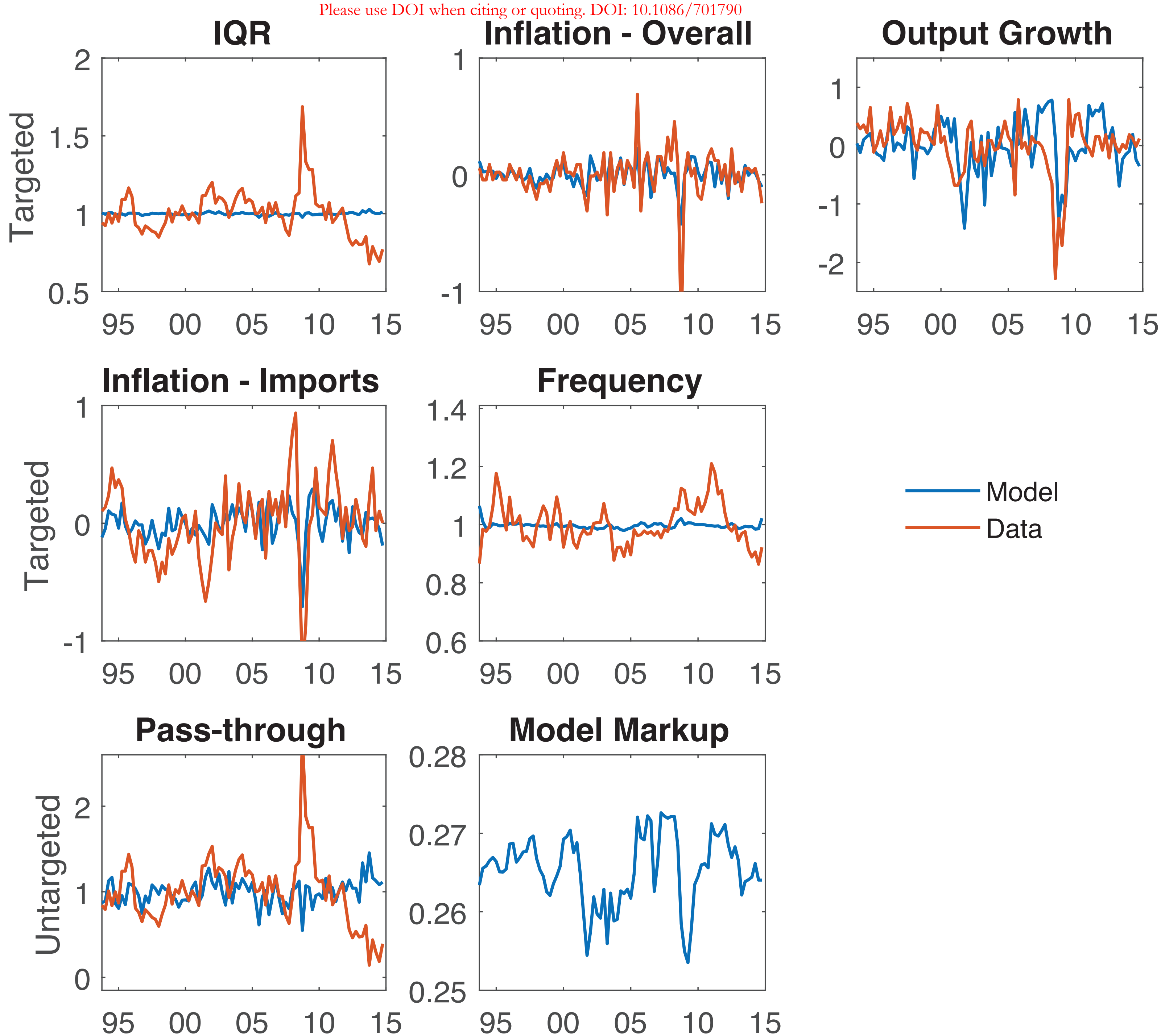
appendix fig 4



appendix fig 5



appendix fig 6



appendix fig 7

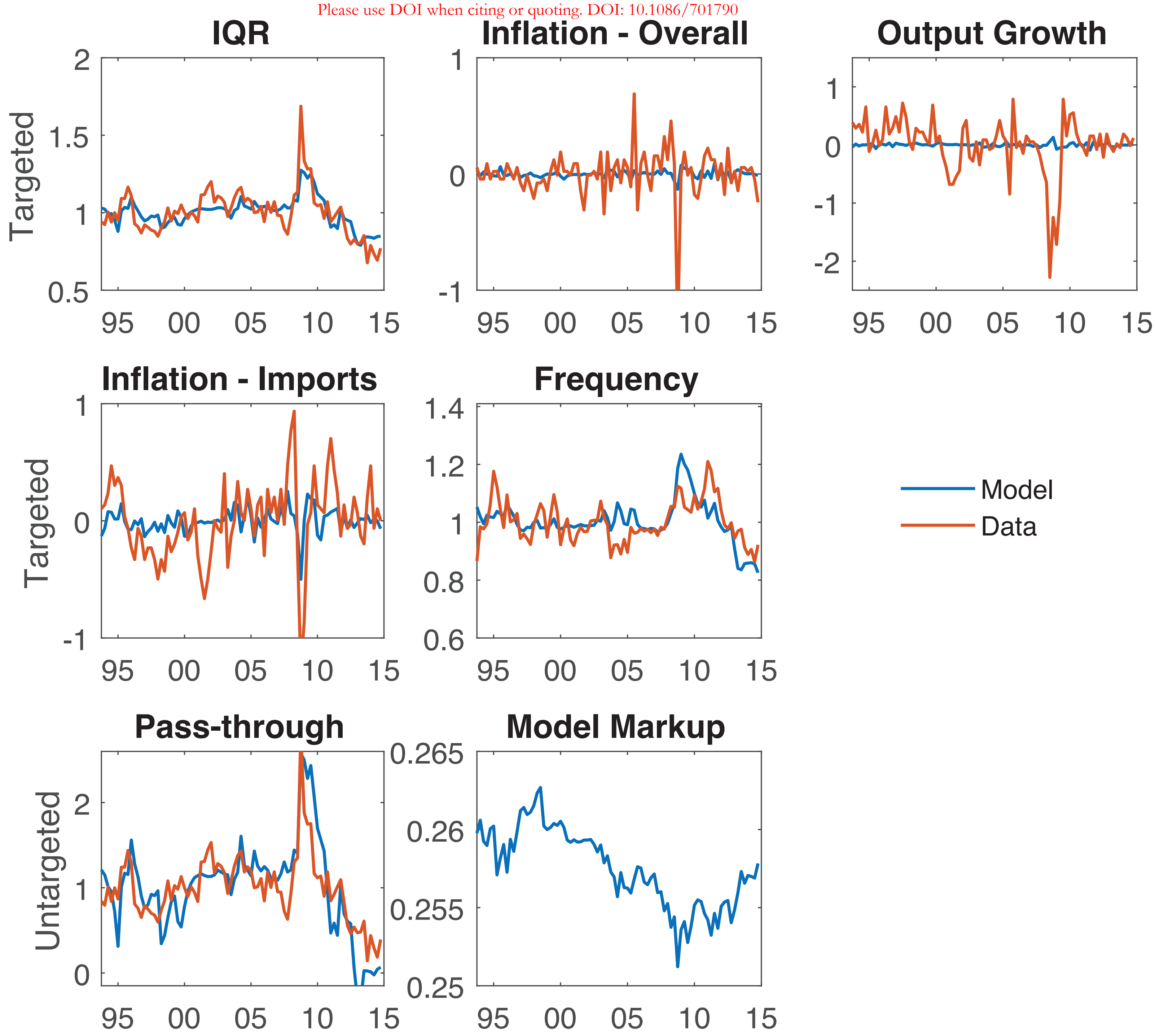


fig 1

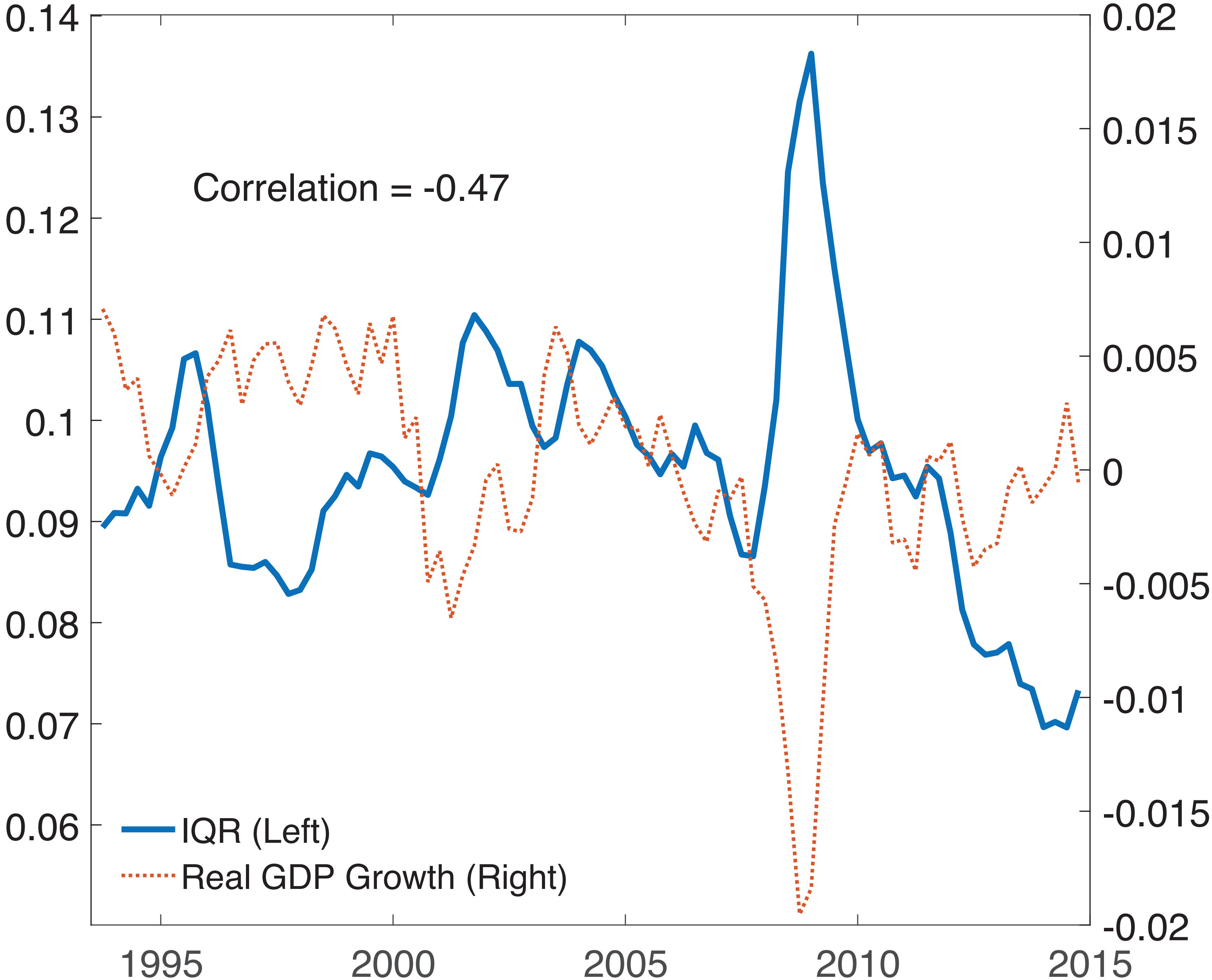

0.14
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
-0.02
1995
2000
2005
2010
2015
Correlation = -0.47
IQR (Left)
Real GDP Growth (Right)

fig 2

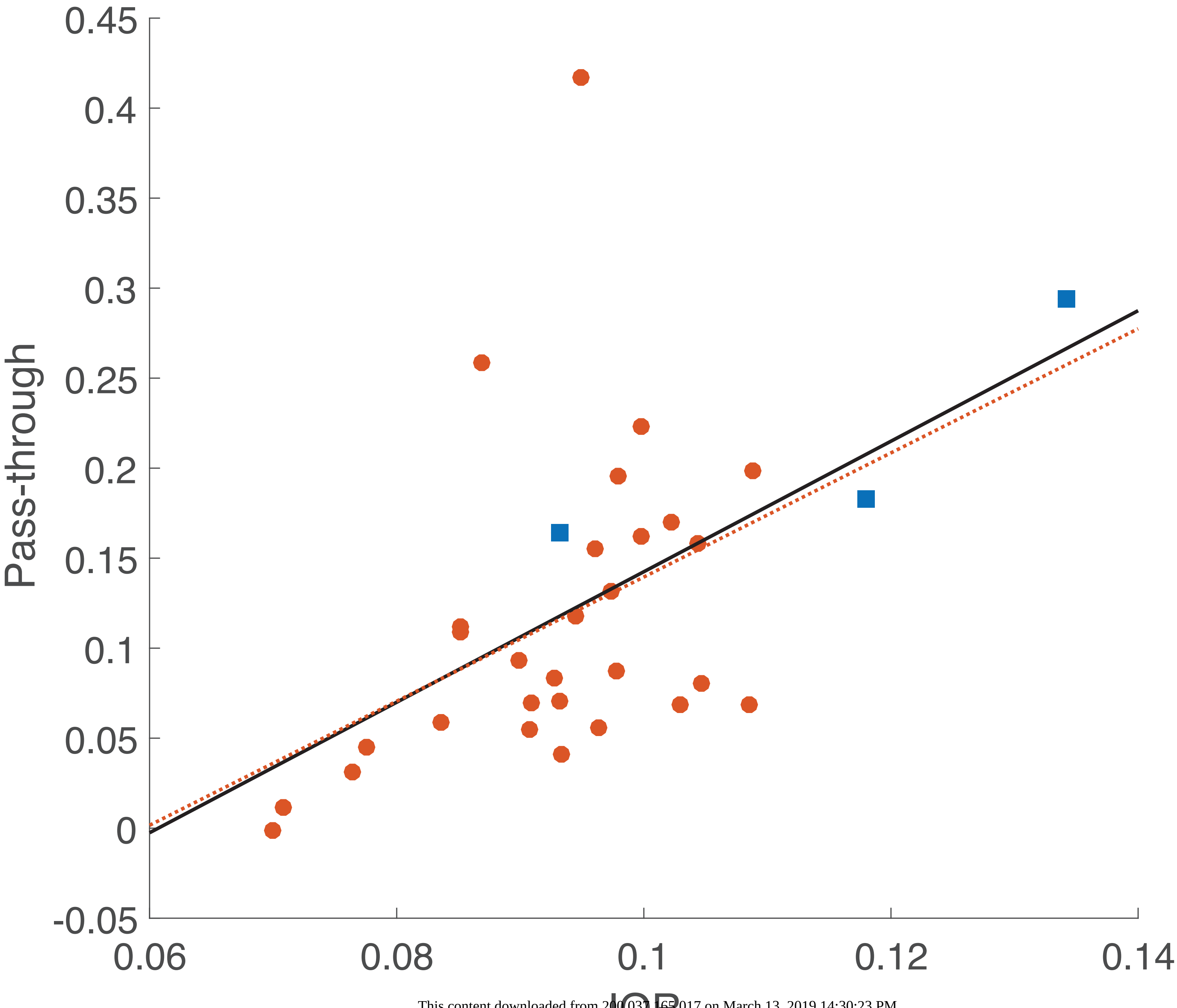

Pass-through
IQR
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
0.06
0.08
0.1
0.12
0.14

fig 3

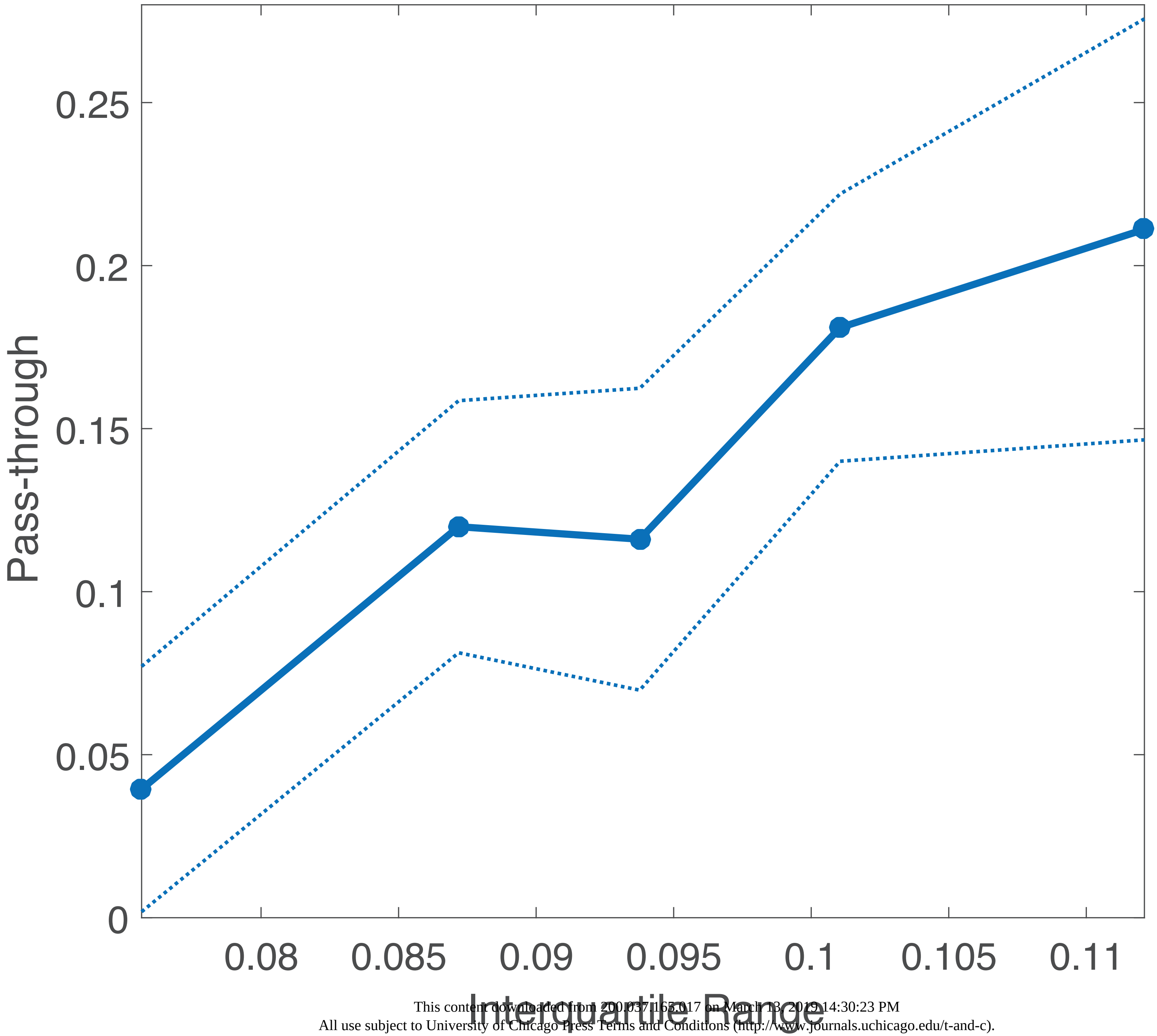

0.25
0.2
0.15
0.1
0.05
0
Pass-through
0.08
0.085
0.09
0.095
0.1
0.105
0.11
Interquartile Range

fig 4

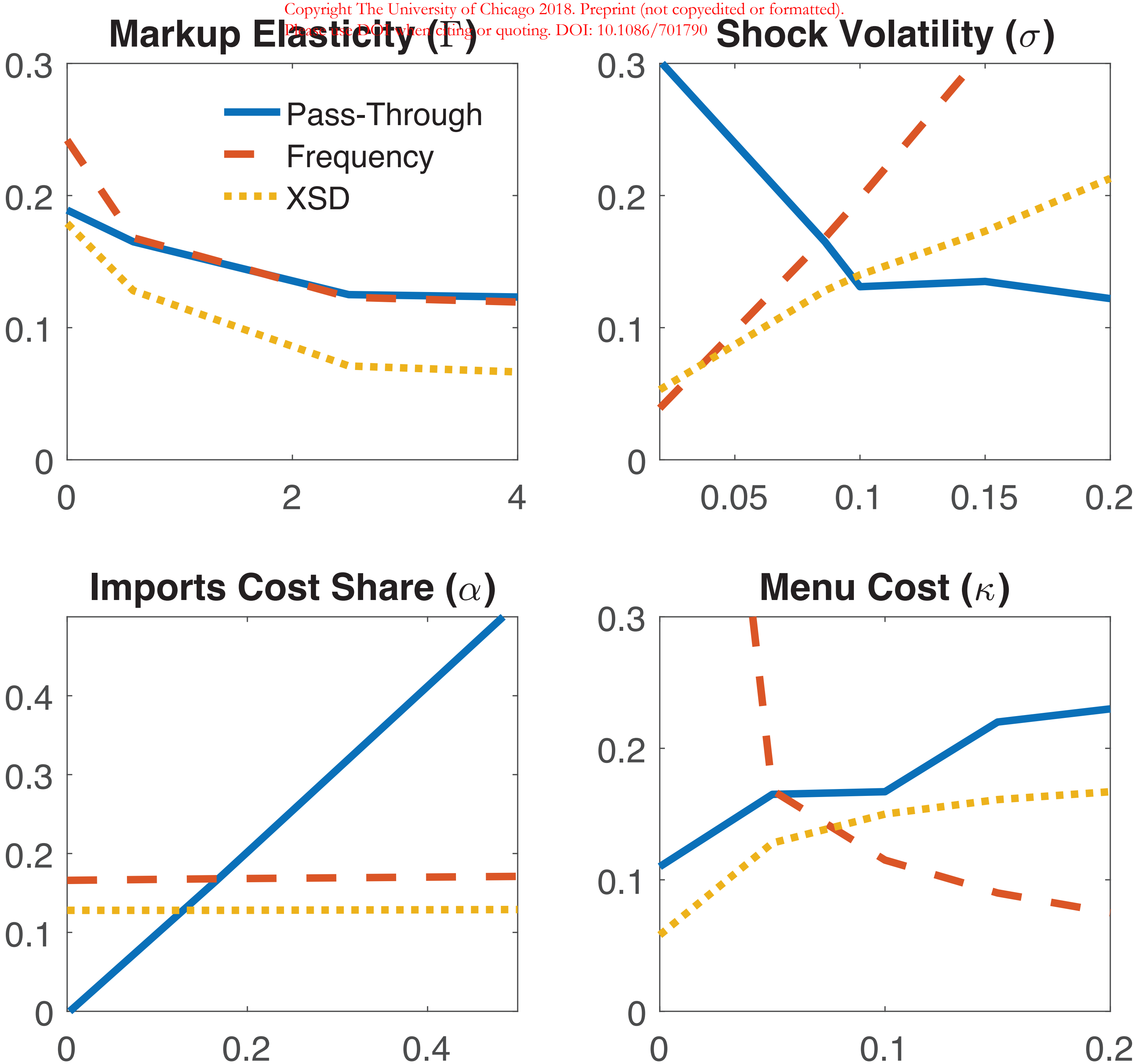

Markup Elasticity (Γ)
Pass-Through
Frequency
XSD
0.3
0.2
0.1
0
0
2
4
Shock Volatility (σ)
0.3
0.2
0.1
0
0.05
0.1
0.15
0.2
Imports Cost Share (α)
0.4
0.3
0.2
0.1
0
0
0.2
0.4
Menu Cost (κ)
0.3
0.2
0.1
0
0
0.1
0.2

fig 5

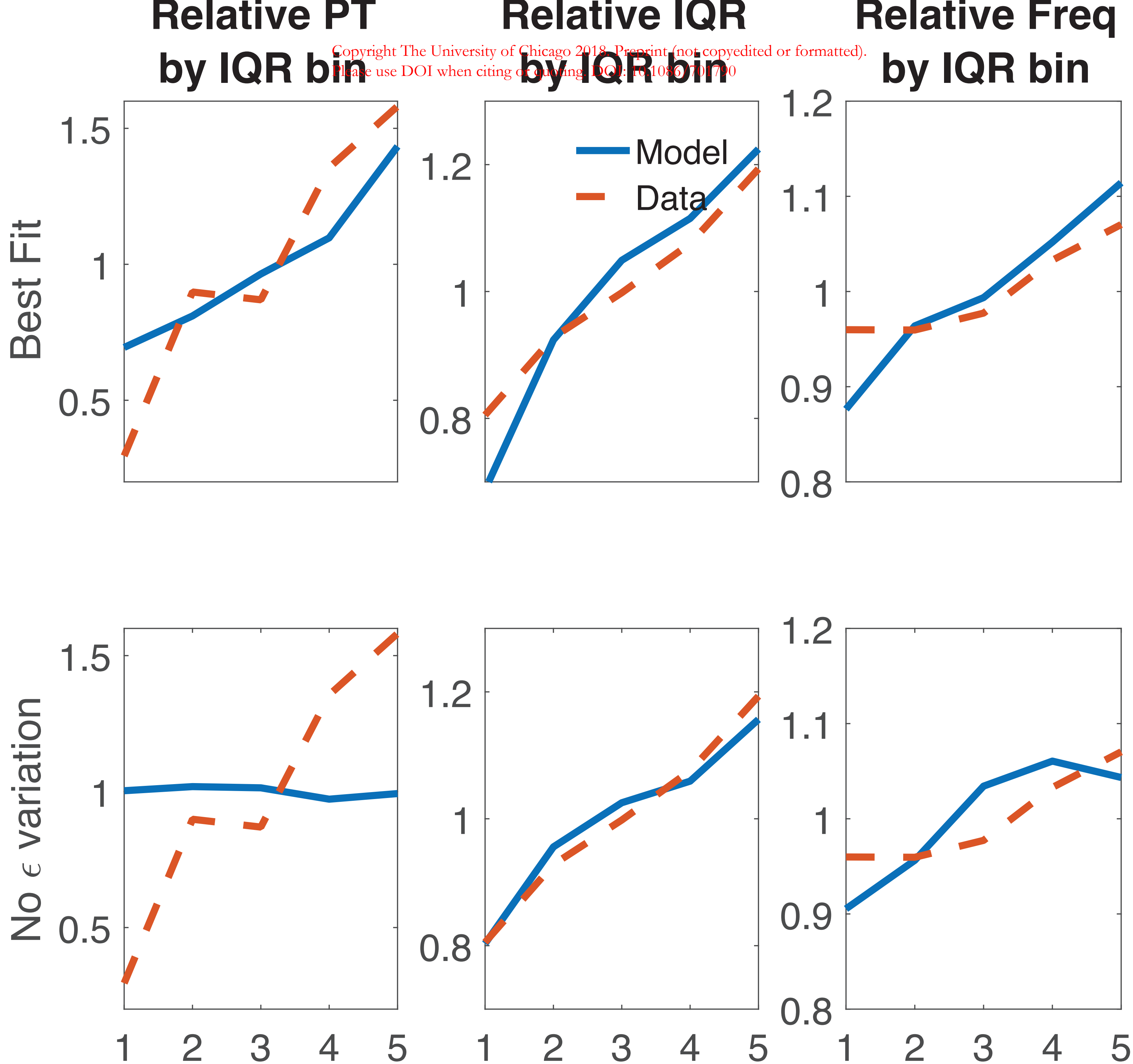
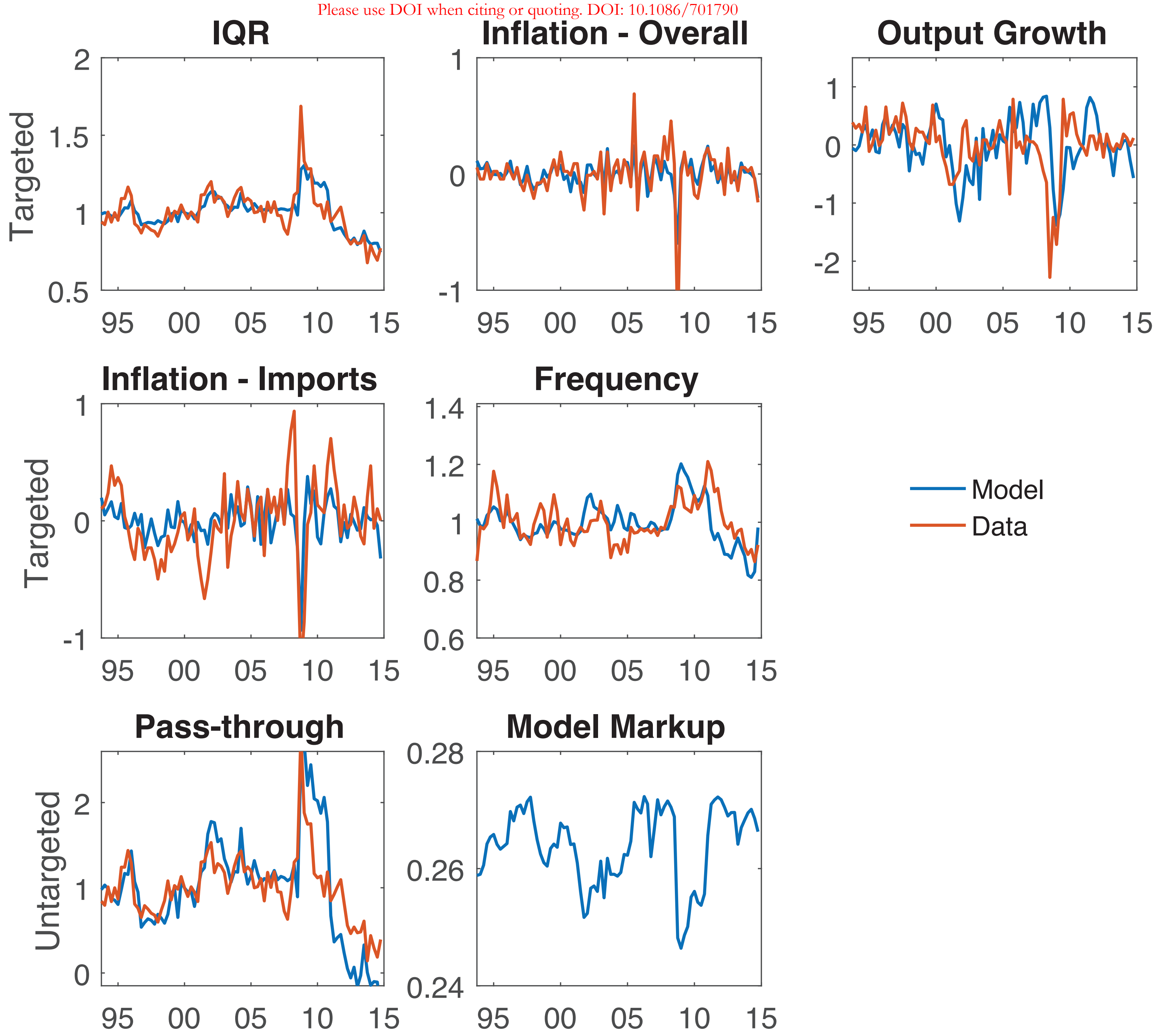

Relative PT by IQR bin
Relative IQR by IQR bin
Relative Freq by IQR bin
Best Fit
No ϵ variation
Model
Data
1.5
1
0.5
1.2
1
0.8
1.2
1.1
1
0.9
0.8
1 2 3 4 5

fig 6


IQR
Inflation - Overall
Output Growth
Inflation - Imports
Frequency
Pass-through
Model Markup
Targeted
Targeted
Untargeted
Model
Data
2
1.5
1
0.5
0
-1
-2
1.4
1.2
0.8
0.6
0.28
0.26
0.24
95
00
05
10
15