Shocks vs. Responsiveness: Online Appendix

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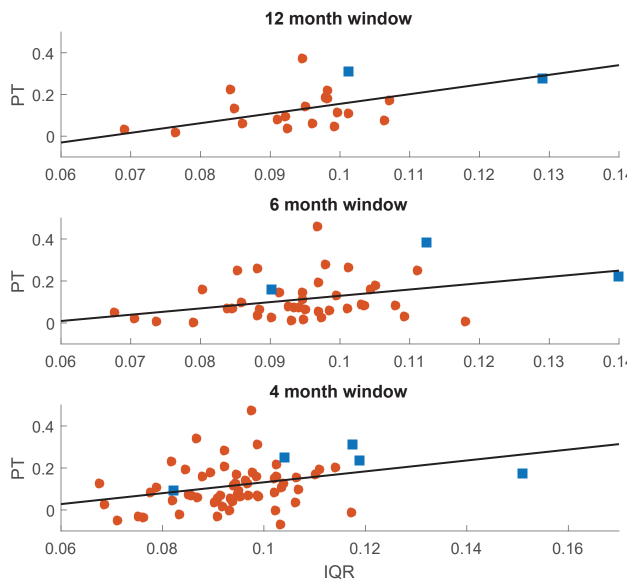
A Empirical Appendix: Online Only

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.

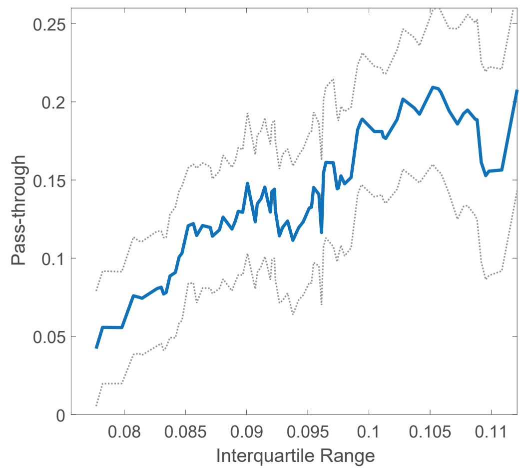
Figure A.1: Dispersion vs. passthrough: Different Windows



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.

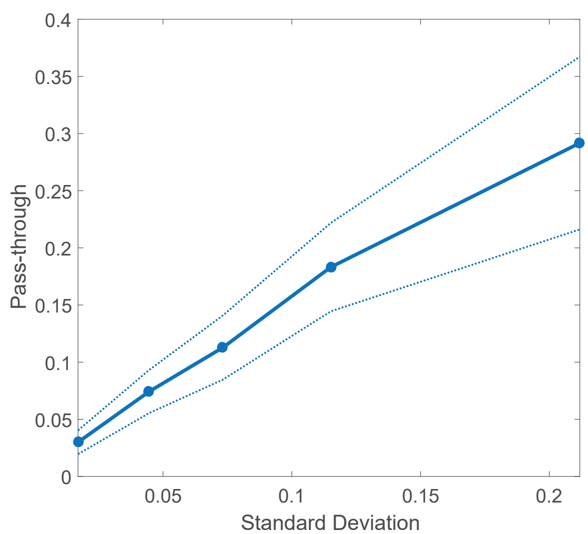
Figure A.2: Non-Parameteric IQR-passthrough Relationship



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, 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, Γ. 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, Γ, in the same form as our baseline model. The difference is that Γ 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:

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

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 $\epsilon_{i,t}\sim G(0,\sigma_{\epsilon t}^2)$.

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:

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

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:

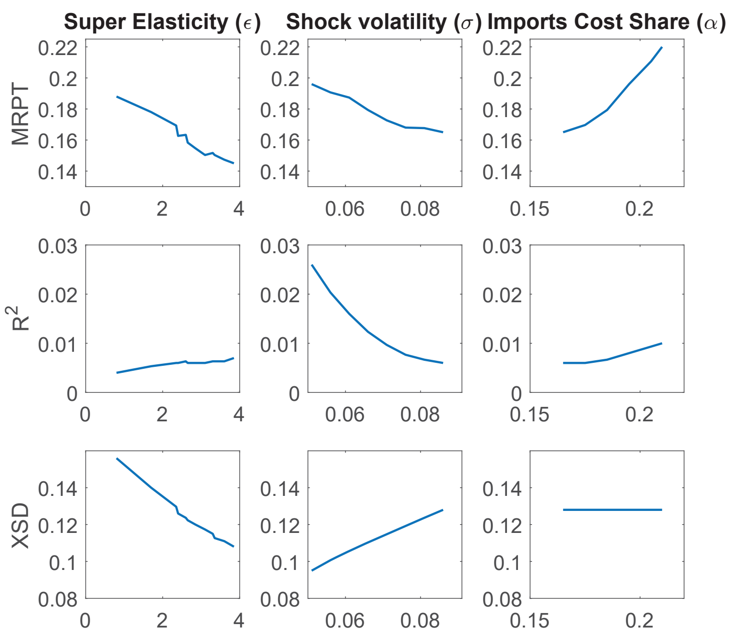
$$\frac{\partial var(\Delta p_i)}{\partial \Gamma_i} = -\frac{2\sigma_{\epsilon t}^2}{(1+\Gamma_t)^3} < 0 \tag{13}$$

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: $\theta = (\kappa_\Delta, \sigma_\Delta, \varepsilon_\Delta)$.

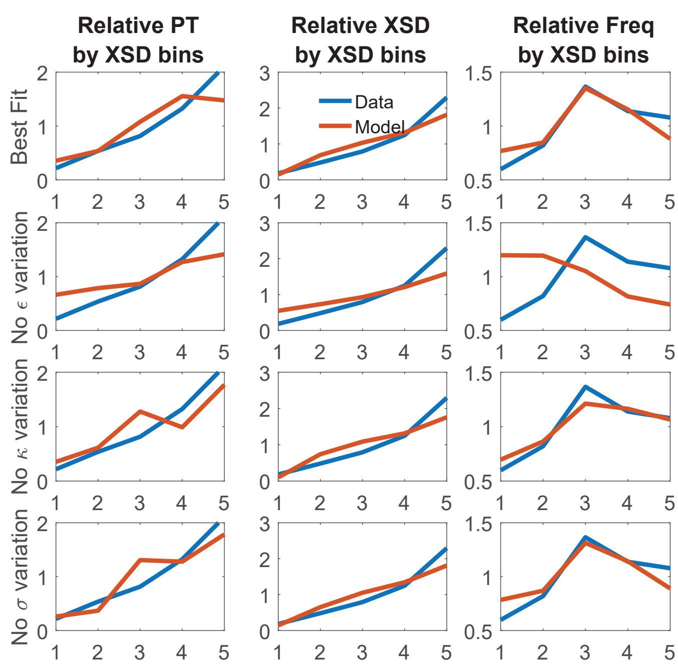
[61] When relevant, we bound the value of $\kappa_l, \varepsilon_l, \sigma_l$ at 0.

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.

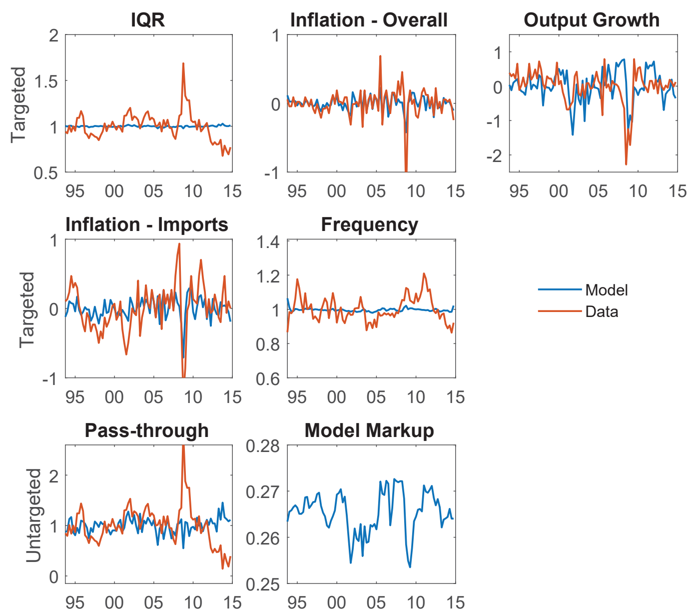
[63] We pick $W(\theta)$ to be the standard efficient weight matrix so that we can apply asymptotic formulas for standard errors but using an identity weight matrix did not change our qualitative conclusions.

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.

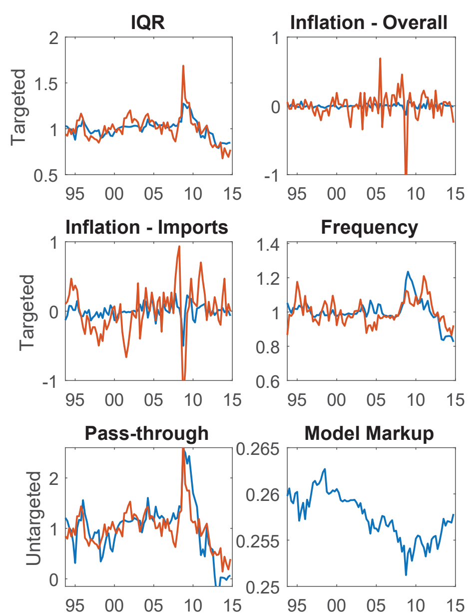
Figure B.6: Time-Series Fit of Model: No Responsiveness Shocks



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$\times\Delta$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×PSL fixed effects with 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 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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