

Menu Costs, Aggregate Fluctuations, and Large Shocks

Online Appendix

SIMPLE MODEL

A1. Moment of the price change distribution

In this section, we derive the key moments of the price-change distribution in the simple model. In particular, we derive the frequency (I) and kurtosis (K) of the price changes and the average size (ΔP) and interquartile range (IQR) of the absolute price change distribution. We derive the moments for the case with no stochastic volatility $\lambda = 1$. In this case, the price gap distribution is Laplace (double exponential) with a scale parameter σ . The density is

$$l(x) = \begin{cases} \frac{1}{2\sigma} e^{-\frac{x}{\sigma}} & \text{if } x \geq 0 \\ \frac{1}{2\sigma} e^{\frac{x}{\sigma}} & \text{if } x < 0 \end{cases}$$

Quadratic loss function x^2 and a menu cost of ϕ^2 implies that the inaction thresholds are given by $\pm\phi$, so the adjustment hazard is

$$\Lambda(x) = \begin{cases} 0 & \text{if } |x| \leq \phi \\ 1 & \text{otherwise} \end{cases}$$

The frequency of price changes is determined by the measure price gaps outside the inaction thresholds

$$I = \int_{\phi}^{\infty} \frac{1}{\sigma} e^{-\frac{x}{\sigma}} dx = e^{-\frac{\phi}{\sigma}}$$

The price-change distribution $dp(x) = l(x)\Lambda(x)/I$ is a combination of tails of an exponential and its mirror image to the vertical axis.

$$dp(x) = \begin{cases} \frac{1}{2e^{-\frac{\phi}{\sigma}}} \frac{1}{\sigma} e^{-\frac{x}{\sigma}} & \text{if } x \geq \phi \\ \frac{1}{2e^{-\frac{\phi}{\sigma}}} \frac{1}{\sigma} e^{\frac{x}{\sigma}} & \text{if } x < -\phi \end{cases}$$

The kurtosis of the price-change distribution is

$$K = \frac{E[x^4]}{(E[x^2])^2} = \frac{2 \int_{\phi}^{\infty} x^4 \frac{1}{2e^{-\frac{\phi}{\sigma}}} \frac{1}{\sigma} e^{-\frac{x}{\sigma}} dx}{\left(2 \int_{\phi}^{\infty} x^2 \frac{1}{2e^{-\frac{\phi}{\sigma}}} \frac{1}{\sigma} e^{-\frac{x}{\sigma}} dx\right)^2} = \frac{I^4 + 6\sigma^2 I^2 + 8\sigma^3 I + 9\sigma^4}{I^4 + 2\sigma^2 I^2 + \sigma^4},$$

which we obtained by repeated application of integration by parts and some straightforward algebra. We also used the symmetry of the distribution.

The distribution of the *absolute* price changes is a tail of an exponential distribution.

$$\text{adp}(x) = \frac{1}{e^{-\frac{\phi}{\sigma}}} \frac{1}{\sigma} e^{-\frac{x}{\sigma}} \quad \text{if } x \geq \phi$$

The average size of absolute price changes is the mean of this distribution

$$\Delta P = \int_{\phi}^{\infty} x \frac{1}{e^{-\frac{\phi}{\sigma}}} \frac{1}{\sigma} e^{-\frac{x}{\sigma}} dx = \phi + \sigma$$

The first quartile (Q_1) of the absolute price change distribution is implicitly determined by

$$\frac{1}{4} = \int_{\phi}^{Q_1} \frac{1}{e^{-\frac{\phi}{\sigma}}} \frac{1}{\sigma} e^{-\frac{x}{\sigma}} dx = 1 - e^{-\frac{Q_1 - \phi}{\sigma}},$$

from which

$$Q_1 = \phi - \sigma \log \frac{3}{4}.$$

Analogously

$$Q_3 = \phi - \sigma \log \frac{1}{4},$$

from which

$$IQR = Q_3 - Q_1 = \sigma \log 3.$$

If $\lambda = 0$, the price-gap distribution is a Pareto-Laplace with a probability distribution

$$PL(x) = \begin{cases} \frac{1-p}{2} e^{\frac{x}{\sigma}} & \text{if } x < 0 \\ \frac{1-p}{2} e^{\frac{x}{\sigma}} + p & \text{if } x = 0 \\ -\frac{1-p}{2} e^{-\frac{x}{\sigma}} + p + \frac{1-p}{2} & \text{if } x > 0 \end{cases}$$

with a mass point at $x = 0$.

If $\lambda \in (0, 1)$, the price gap distribution is a mixed Laplace with a density

$$ml(x) = \begin{cases} \frac{1-p}{2\sigma} e^{-\frac{x}{\sigma}} + \frac{p}{2\sigma\lambda} e^{-\frac{x}{\sigma\lambda}} & \text{if } x \geq 0 \\ \frac{1-p}{2\sigma} e^{\frac{x}{\sigma}} + \frac{p}{2\sigma\lambda} e^{\frac{x}{\sigma\lambda}} & \text{if } x < 0 \end{cases}$$

For cases $\lambda \in [0, 1)$, the moments can be obtained analogously to the $\lambda = 1$ case, and the derivations are available from the authors on request.

FULL MODEL

B1. Equivalence of inflation effects of money and tax shocks

In this section, we show that for our baseline parametrization, permanent money shocks and value-added tax shocks have equivalent effects on the inflation path - even though their effects on the output is different. The proof guesses the same price level paths and verifies that the money supply and the tax rate have equivalent effects on the optimal price choices, justifying the equal-price-effect assumption.

Nominal wage moves together with the money supply, under our assumptions on the labor supply equation with separable utility that is logarithmic in consumption and linear in labor ($\psi = 0$). In this case

$$(B1) \quad W_t = \mu P_t Y_t = \mu M_t.$$

Substituting this into equation (6) about the periodic normalized profit, one can easily re-write the profit equation as

$$(B2) \quad \bar{\Pi}_t(i) = \left(\frac{1}{1 + \tau_t} \right) \sum_{g=1}^G \left[p_t(i, g)^{1-\gamma} - \frac{\mu M_t (1 + \tau_t)}{P_t} p_t(i, g)^{-\gamma} \right] \left(\frac{1}{G} \sum_{g=1}^G p_t(i, g)^{1-\gamma} \right)^{(\gamma-\theta)/(1-\gamma)}.$$

Let's guess that the present and future path of the price level $\{P_t\}$ is the same for a permanent tax shock and a permanent money level shock. The optimal price choices of firms depend on their normalized value function, which is a present discounted value of their future profits. As the derivation shows, the tax rate influences the level of profits, but its influence on the optimal price choice is equivalent to that of the money supply.¹ As we also assume lump-sum redistribution of taxes, the variables will not influence the budget constraints either. It means that the assumption of equivalent price level development is indeed verified. So we are justified to use evidence gained from value-added tax shocks to test the predictions of our model to large permanent money shocks.

B2. The flexible price equilibrium

The algebraic solution for the flexible price equilibrium provides useful information about the long-term pass-through of the permanent tax- and money shocks. Money shocks, naturally, have no real effects under flexible prices, so we will have full pass-through to the price level. A permanent value-added tax shock, for our parametrization, will imply a unit drop in the real output, so under constant money supply, we will have full pass-through into the gross nominal prices in this case as well.²

To gain some insight into why value-added tax shocks imply a unit drop in output, it is useful to look at the firms' static profit maximization problem. Under flexible prices, firms will choose prices to maximize this, implying the following optimal relative price:

$$(B3) \quad p_t i, g^* = (1 + \tau_t) \frac{\gamma}{\gamma - 1} w_t,$$

where $w_t = W_t/P_t$ is the real wage. The equation shows that each firm want to increase their *relative* prices as a response to a tax increase. As all firms cannot do this in equilibrium, real wages have to drop endogenously. It requires lower labor demand and output; and as household wage income will drop in parallel, the aggregate demand will adjust sufficiently to satisfy general equilibrium.

As all firms will choose the same productivity-adjusted relative price, the Dixit-Stiglitz-aggregate of these relative prices – that needs to be equal to 1 by definition – is also $\gamma w_t (1 + \tau_t) / (\gamma - 1) = 1$. We find that

$$(B4) \quad w_t = \frac{\gamma - 1}{\gamma(1 + \tau_t)}.$$

From the labor market equation, we know that $w_t = W_t/P_t = \mu Y_t$, and any demand is going to

¹For that to be exactly true, we need to assume that menu costs are tax deductible, so their effective costs drop with higher value-added taxes together with the value functions.

²We are also using the flexible price solution as starting values for the iterative procedures in our numerical solution method.

be satisfied at this wage. The equilibrium output is, thus, given by

$$(B5) \quad Y_t = \frac{\gamma - 1}{\gamma\mu(1 + \tau_t)}.$$

The nominal price level can be obtained as

$$(B6) \quad P_t = \frac{M_t}{Y_t} = M_t \frac{\gamma\mu(1 + \tau_t)}{\gamma - 1}.$$

The expected growth rates are

$$(B7) \quad E(g_Y) = -E(g_{1+\tau_t}), \quad E(\pi_t) = g_M + E(g_{1+\tau_t})$$

This shows that a permanent increase in the tax will imply a full and immediate inflation pass-through under flexible prices.

B3. Numerical solution algorithm

This subsection describes our numerical solution algorithm. It consists of two parts.

First, we solve for the steady-state aggregate variables π^{SS} , w^{SS} and Γ^{SS} . As we assumed no aggregate uncertainty, aggregate variables will converge to their steady-state values. The steady-state inflation rate is equal to the growth rate of money stock: $\pi^{SS} = g_M = g_{PY}$. Then we calculate the steady-state real wages (w^{SS}) and the distribution of firms over their idiosyncratic state variables (Γ^{SS}) with the following iterative procedure:

- 1) We start with a guess for w^{SS} , w_0 . Initially, this guess is equal to the flexible-price steady-state of w , that we can calculate analytically (see the previous subsection).
- 2) Given this guess and the steady-state inflation rate, we use a fine grid on relative prices³ and idiosyncratic shocks⁴ to solve for the optimal pricing policies of individual firms. We use value function iteration with quadratic and linear interpolation.
- 3) With the resulting policy functions, we calculate the steady-state distribution of firms over their idiosyncratic state variables. For this, we use the same set of grids as for the value function iteration. We again do this numerically: starting from a uniform distribution, we calculate the resulting distribution after idiosyncratic shocks hit, and also after firms re-price. Then again calculate the resulting distributions after a new set of idiosyncratic shocks and new re-pricing. We do this until convergence.
- 4) We calculate the (Dixit-Stiglitz) average relative price in the resulting steady-state distribution. If this is smaller (larger) than 1, then we increase (decrease) our initial guess (w_0) of the real wages.
- 5) We repeat these steps until the average relative price in the calculated steady-state distribution equals 1.

³We have 2,000 gridpoints when idiosyncratic shock innovations are permanent (i.e., when the normalized relative price is the only idiosyncratic state variable).

⁴In the temporary idiosyncratic shock case (when the idiosyncratic shock is also a state variable) we have 101 gridpoints for the quality shocks, and 500 for the relative prices.

In the second part of our numerical algorithm, we calculate the equilibrium paths of aggregate variables after an unexpected shock at $t = 0$ to the money supply, assuming that initially, all aggregate variables were in their steady states. We calculate the equilibrium paths of π (inflation), w (real wages) and Γ (distribution of firms over their idiosyncratic state variables) with the following shooting algorithm:

- 1) We assume that aggregate variables will reach their steady-state in a finite (large) number of periods, T .
- 2) We start with a guess for the equilibrium inflation path $\{\pi_1, \dots, \pi_T\}$. Our initial guess is the full immediate pass-through.
- 3) Given this guess, we calculate the resulting equilibrium path of the real wages: $\{w_1, \dots, w_T\}$. As $w_t = \mu Y_t$, we do this by calculating the equilibrium real GDP path, which we know from the equilibrium inflation path (and the constant nominal growth assumption).
- 4) Given the inflation and real wage paths, we calculate the path of value and policy functions. We do this by backward iteration from T , where the economy and the value functions are assumed to converge to a steady state.
- 5) Starting from period 1, and using the steady-state distribution of firms over their idiosyncratic state variables as initial distribution, we use the sequence of policy functions (together with the idiosyncratic shock processes) to calculate the resulting path of Γ , the distribution of firms over their idiosyncratic state variables.
- 6) From the resulting sequence of distributions, we calculate the resulting inflation path and compare it with our initial guess. If the two are different, we update our guess to the linear combination of our previous guess and the resulting inflation path.
- 7) We do these iterations until the resulting inflation path is the same as our initial guess.

B4. Source of monetary non-neutrality

We decompose the impact of the monetary policy shock on the price level to three key margins of adjustment.⁵ The intensive margin characterizes adjustment in the size of the price changes, the extensive margin characterizes the change in the fraction of adjusting firms, and the selection effect measures the variation in the composition of the adjusters. The inflation rate is a function of the price gaps (the adjustments x_1, x_2 that firms would make if menu costs disappeared for a period), their hazard function $\Lambda(x_1, x_2)$ and distribution $l(x_1, x_2)$ (see, for example, Costain and Nakov, 2011).⁶ The inflation rate equals

$$(B8) \quad \pi = \int \int (x_1 + x_2) \Lambda(x_1, x_2) l(x_1, x_2) dx_1 dx_2,$$

⁵In the simple model, the marginal aggregate shock size guaranteed that the aggregate frequency does not respond to the monetary policy shock. For reasonable shock sizes, we can not rule out the impact of this channel.

⁶The price gaps are functions of the individual state variable p_{-1} (the last period's quality-adjusted relative price) and aggregate states that we suppress for notational convenience.

and the impact of an aggregate shock in period t can be decomposed into an intensive, extensive and selection margins, as

$$(B9) \quad \pi_t - \pi = \underbrace{\overline{\Lambda(x_1, x_2)} \Delta \bar{x}}_{\text{intensive}} + \underbrace{\Delta \overline{\Lambda(x_1, x_2)} \bar{x} + \overline{\Delta \Lambda(x_1, x_2)} \Delta \bar{x}}_{\text{extensive}} + \underbrace{\Delta \int \int (x_1 + x_2) \left(\Lambda(x_1, x_2) - \overline{\Lambda(x_1, x_2)} \right) l(x_1, x_2) dx_1 dx_2}_{\text{selection}},$$

where $\overline{l(x_1, x_2)} = \int \int l(x_1, x_2) dx_1 dx_2$ and $\bar{x} = \int \int (x_1 + x_2) dx_1 dx_2$, and Δy for any variable y denotes difference from the steady state $y_t - y$.

The intensive margin is the product of the average frequency and the change in the average price gap: in a Calvo-model with a fixed frequency and random selection, this would be the only component of the pass-through. The extensive margin is defined here as the aggregate effects caused by the changes in the price-change frequency. It is the sum of two products: the product of the frequency increase and the average price gap and the product of the frequency change and the average price gap. For small shocks that do not influence the aggregate frequency, this term is negligible. The third factor is the selection effect, which is the consequence of ‘new’ price changers having higher than average price gaps. The third term expresses this by measuring the increased correlation between the price gap and the adjustment hazard after a shock.

To obtain a single price-flexibility measure from impulse responses, we calculate an average pass-through of a shock. For this, we first calculate a ‘marginal’ pass-through (γ_t^m) for each period t , measured as the inflation effect in period t relative to the fraction of cumulative money shocks yet to be passed through:

$$(B10) \quad \gamma_t^m = \frac{\pi_t - \bar{\pi}}{\left(\sum_{i=0}^t \Delta m_i - \sum_{i=0}^{t-1} (\pi_i - \bar{\pi}) \right)}.$$

We weight these marginal pass-throughs based on their relative size ($\omega_t = (\pi_t - \bar{\pi}) / (\Delta m / (1 - \rho))$) to arrive at a measure of aggregate price flexibility:

$$(B11) \quad \bar{\gamma} = \sum_{t=1}^T \omega_t \gamma_t^m.$$

This weighted average marginal pass-through is one in case of full price flexibility. In the Calvo model, the measure equals to the periodic marginal pass-through, which is constant over time.

The impulse responses presented on Figure 7 generate price flexibility ($\bar{\gamma}$) of 40 percent in our baseline mixed normal model, and 12, 62 and 11 percents in the Poisson, Gaussian, and Calvo models, respectively. We find that the difference in the selection effect drives the difference across models. For small money growth shocks, extensive margin effect is negligible. The intensive margin effect, in turn, is very close in each model, the differences coming only from the variation in the frequency of price changes at 0 inflation rates (they are 15.5 percent in our baseline and 17.5 percent in the Gaussian models, but only 11 percent with Poisson and Calvo). The selection effects, however, are very different: contributing to the measured pass-through by 24 percentage points in our baseline mixed normal case and by 44.5 percentage points in the Gaussian case, while they are only 1 percent in the Poisson case. This confirms that similarly to the simple model, the extent of stochastic volatility strongly influences the extent of monetary non-neutrality of the

models through its impact on the selection effect.

B5. Calibrated parameters of the robustness exercises

This section presents the calibrated parameters of the robustness exercises. The parameters were calibrated to match the observed frequency of price changes and size of absolute price changes (in all), the kurtosis of price changes (Poisson and mixed normal) and interquartile range of the absolute price-change distribution (mixed normal). The table shows that there are some differences between the parameters across different models, but this does not lead to qualitative differences between the predicted monetary non-neutrality as Section V shows.

TABLE B1—CALIBRATED PARAMETERS OF THE ROBUSTNESS EXERCISES

	Baseline			Multi-product, aggregate fluctuations, 0 inflation calibration			Multi-product, aggregate fluctuations, positive inflation calibration		
	Mixed	Poisson	Normal	Mixed	Poisson	Normal	Mixed	Poisson	Normal
ϕ	2.4%	1.6%	5.0%	2.3%	1.0%	5.0%	2.4%	1.9%	5.0%
σ_A	4.3%	4.4%	3.8%	4.4%	4.7%	3.8%	4.2%	4.3%	3.8%
p	91.2%	90.6%	0	92.3%	90.8%	0	91.3%	90.7%	0
λ	8.8%	0	1	9.7%	0	1	7.5%	0	1
	Stochastic menu cost			Stochastic menu cost aggregate fluctuations, 0 inflation calibration			Stochastic menu cost aggregate fluctuations, positive inflation calibration		
	Mixed	Poisson	Normal	Mixed	Poisson	Normal	Mixed	Poisson	Normal
ϕ	1.0%	0.7%	2.45%	0.9%	0.2%	2.43%	0.9%	0.7%	2.44%
σ_A	4.3%	4.4%	3.6%	4.5%	4.8%	3.6%	4.3%	4.3%	3.6%
p	90.8%	90.5%	0	91.8%	90.7%	0	90.8%	90.5%	0
λ	7.4%	0	1	8.7%	0	1	6.4%	0	1
κ	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%

TABLE B2—FORECAST EQUATION PARAMETERS IN MODELS WITH AGGREGATE FLUCTUATIONS (ZERO INFLATION CALIBRATION)

	Multi-product		
	Mixed	Poisson	Normal
α	-0.41	-0.41	-0.41
α_w	0.65	0.66	0.59
α_m	0.49	0.88	0.33
α_{m^2}	0.01	0.01	0.01
α_{m^3}	-0.2	-1.0	-0.03
R^2	1.00	0.99	1.00

	Stochastic menu cost		
	Mixed	Poisson	Normal
α	-0.41	-0.41	-0.41
α_w	0.69	0.69	0.61
α_m	0.45	0.85	0.32
$\alpha_{m^2} \cdot 100$	0.00	-0.03	0.01
$\alpha_{m^3} \cdot 10000$	-0.16	-1.34	-0.02
R^2	1.00	0.98	1.00

TABLE B3—RANDOM MENU COSTS: MOMENTS IN THE MONTHS WITH TAX CHANGES

Moment	Size	Data	Mixed	$\kappa = 0.8\%$		$\kappa = 4.2\%$
				Poisson	Normal	Poisson
Inflation pass through	+3%	74%	77%	165%	40%	81%
	+5%	99%	97%	142%	47%	102%
	-5%	33%	27%	12%	38%	12.6%
Frequency	+3%	52%	39%	80%	18%	37%
	+5%	62%	62%	89%	23%	62%
	-5%	27%	20%	11%	16%	13%
Kurtosis	+3%	10.6	13.0	24.4	5.8	11.7%
	+5%	8.1	18.6	26.5	10.4	18.1%
	-5%	9.2	6.4	3.4	3.9	4.0%
Abs. interquartile range	+3%	5.1%	2.3%	1.9%	2.8%	2.6%
	+5%	5.9%	2.9%	1.9%	3.2%	2.9%
	-5%	5.0%	4.3%	11.3%	2.8%	12.7%
Absolute size	+3%	6.5%	7.8%	6.7%	10.4%	8.7%
	+5%	9.0%	8.2%	7.6%	10.9%	8.5%
	-5%	8.6%	8.1%	10.6%	10.5%	9.3%

C1. Macroeconomic environment in Hungary between 2002-2006

In this section, we describe the macroeconomic environment in Hungary around the value-added tax changes between 2004-2006.

Between 2002 and 2006, Hungarian real GDP grew by an average of 4.2 percent per year. As panel A of Figure C1 shows, this growth rate was remarkably stable: the yearly growth rates fluctuated between 3.9 percent (2003 and 2006) and 4.8 percent (2004). Meanwhile, the core inflation (see panel B) averaged at a low 4.1 percent.⁷

This relatively quick real growth can partly be explained by the rapid growth rate of private debt: the approximately 30 percent private debt-to-GDP ratio in 2002 increased steadily to around 55 percent by 2006 (panel D).⁸ In parallel, the budget deficit was also running high (between 6.4 percent of GDP in 2005 and 8.9 percent of GDP in 2003), and government debt increased from 52 percent of GDP in 2002 to around 62 percent of GDP in 2006. Under these circumstances, it is hardly surprising that household consumption (panel E) and the volume of retail trade also increased steadily during this period.⁹

The 2004 value-added tax increase was motivated by a minimum tax rate requirement of the European Union. It was introduced in parallel to other related measures, some tax increases, some tax decreases with minor net effect on the net personal disposable income (see panel F). The 2006 value-added tax changes were aimed at simplifying the tax code. The tax decrease was implemented in January, with only minor additional tax measures, partly to improve the popularity of the government before the April 2006 general elections (which resulted in the government being re-elected). The tax increase in September 2006 was announced jointly with other measures which were aimed at reducing the budget deficit. Most of the tax measures influencing personal income took effect only in January 2007, while the VAT-increase (September) and some regulated price increases (e.g., heating gas, electricity) were implemented mid-year.

The inflation targeting central bank communicated explicitly that it would not react directly to the value-added tax changes, as their direct effect would disappear from the inflation rate at the policy horizon. It added that it would monitor any second-round effects through changing expectations. Indeed, there are no immediate changes in the policy rate right after the value-added tax changes, and during this period it seems that the central bank was mostly responding to depreciating exchange rates (see panel C). The exchange rate was mostly stable during the period, temporary shocks to it were counteracted by the interest policy of the inflation targeting central bank.

One could claim that factors missing from our model had a significant influence on the observed pass-through of the VAT-changes. First, we saw an approximately 10% depreciation of the local currency, the Hungarian Forint (relative to the Euro) in the summer of 2006, i.e., just before the five-percentage-point tax hike. However, this depreciation was only temporary and counteracted by interest rate hikes by the exchange-rate smoothing central bank. Furthermore, given the long time lag at which exchange rate movements pass through into processed food prices in Hungary, we can safely assume that the exchange rate had a minor impact on the CPI developments. Second, there were a series of regulated electricity and gas price increases in August and September of 2006 (together with the VAT-increase). However, they affected only the *consumer* prices of gas and electricity and had no impact on producer prices, so this could only have had a minor impact on

⁷Panel A shows the level of GDP normalized to 100 in 2001Q4. Panel B shows the month-on-month core inflation rates. Their average is 0.345 percent, or approximately 4.1 percent annually.

⁸Panel D shows the sum of household and corporate debt as a fraction of GDP.

⁹Panel E shows the level of households' consumption expenditures normalized to 100 in 2001Q4.

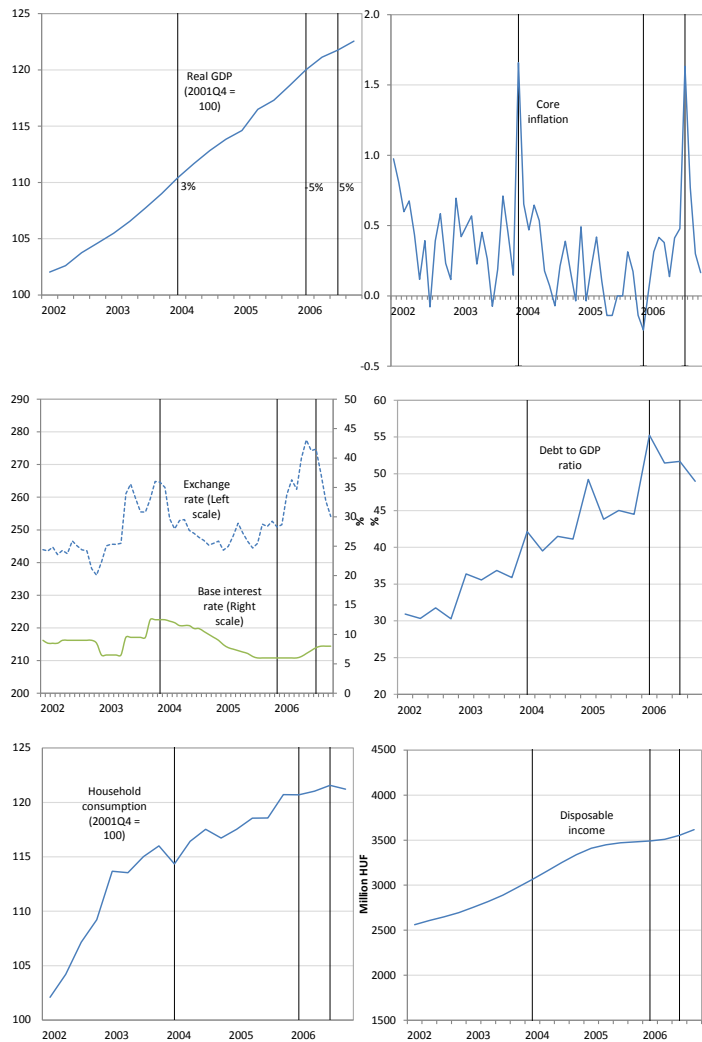


FIGURE C1. THE MACROECONOMIC ENVIRONMENT IN HUNGARY

Note: The figure plots development of key indicators in Hungary around the value-added tax changes. The 12% rate was increased to 15% in January 2004 (first horizontal bar), the 15% rate was increased to 20% in September 2006 (third horizontal bar) and the 25% rate was decreased to 20% in January 2006 (second horizontal bar). The indicators show a steady growth in GDP, retail consumption with small inflation rates (4%) and relatively stable exchange rates.

retail firms pricing behavior in September 2006. Finally, fiscal policy measures in parallel with the VAT-changes have not had a significant impact on the net disposable income (see panel F), so their effect on prices could only have been minimal. All in all, we argue that most of the observed movements in the inflation rates were due to the VAT-changes, and other factors can be safely

disregarded.

C2. A 5 percentage-point tax increase in 2009

Although the product groups affected by the 2004 and 2006 VAT changes were similar, these groups were not identical. This may lead to composition bias in estimating moments. In this subsection, we use evidence from a five-percentage-point VAT increase in 2009 to evaluate the possible size of this bias in estimating the asymmetry in inflation effects in 2006. This additional evidence helps us because now we have products that were hit by both a VAT-decrease and a VAT-increase, so we can directly compare their price responses. The difficulty, however, is that during the 2009 increase, the economy was undergoing a severe recession that might have a substantial impact on the inflation pass-through. Controlling for the business cycle effects implies a comparable level and asymmetry of the pass-through as in our baseline experiment.

In July 2009, in an attempt to increase government revenues during the financial crisis, Hungarian authorities decided to increase the by now unified VAT-rate of 20 percent to 25 percent. As the second column of Table C1 indicates, 102 of the 128 products in our original processed food sample were hit by this new five-percentage-point tax increase.¹⁰ Our estimate for the inflation pass-through of this tax change is 56.6%, which is relatively small. One possible explanation for this moderate pass-through is the ongoing massive recession (6.8 percent fall in Hungarian real GDP in 2009; as opposed to the 3.9 percent real GDP growth in 2006).

TABLE C1—INFLATION PASS-THROUGH IN 2009 AND 2006

	Tax inc in 2009	Inc09-Dec06	Inc09-Inc06
Number of items	102	29	73
CPI-weight	10.75	3.37	7.38
Infl PT in 2009 (+5%)	56.6%	68.8%	51.1%
Infl PT in 2006 Jan (-5%)	–	32.6%	–
Infl PT in 2006 Sep (+5%)	–	–	88.0%

The third column of Table C1 contains information about the inflation pass-through for those 29 processed food items that were hit by both the 5 percentage-point tax decrease in January 2006 and the 5 percentage-point tax decrease in July 2009. Even in this group (not subject to composition bias), we see substantial asymmetry, 32.6 percent vs. 68.8 percent. This happened even though the pass-through in 2009 was in general much smaller than in 2006: according to column 4, for the 73 items that were hit by both tax increases of September 2006 and July 2009, the respective pass-throughs were 51.1 percent and 88.0 percent. So the substantial asymmetry in column 3 is likely to be underestimated due to business cycle effects, thus our original estimate (33 percent vs. 99 percent) seems reasonable.¹¹

ASYNCHRONOUS VARIATION IN PRICE DISPERSION

In this section, we offer some suggestive evidence supporting our choice of an idiosyncratic shock that is drawn from a distribution with random volatility. In particular, we show that the standard

¹⁰The remaining 26 items (all of the basic food items) got into a newly created 18 percent VAT-category. In essence, this created a multiple-rate VAT-system again with rates 18 percent and 25 percent, but now a much smaller proportion of the consumption basket had the lower VAT-rate than before 2006.

¹¹If we assumed that the 2009 pass-through was proportionally lower for each single product (i.e., only $51.1/88.0=58.1\%$ of the 2006 pass-through), then the asymmetry in the third column would be 32.6 percent vs. 118.5 percent, not far from our original estimate.

deviation of price changes varies over time, and it does so asynchronously across products. This is inconsistent with standard menu cost models, in which a price change induced by idiosyncratic shocks has uniform dispersion. We show evidence for this using three micro-level price data sets. The first is our baseline dataset underpinning the calculation of the Hungarian consumer price index (CPI). The data is available between January 2002 and December 2014 and covers over 700 narrow product categories from non-regulated products of the CPI (covering over 70 percent of the aggregate CPI basket). We calculate the weighted¹² standard deviation of log price changes ($dp_{it} = \log p_{it} - \log p_{it-1}$) in 107 3-digit product groups (e.g., milk).¹³ We detrend each product-level time series and clean them from seasonal variation and the contemporaneous impacts of VAT changes.¹⁴ To measure the level of asynchronicity across products, we regress each product-level standard deviation separately on the aggregate standard deviation, and calculate the fraction of the time-series variation in dispersion that is explained by the aggregate, on average. We find that the weighted standard deviation of the whole cross-section explains only 2.5 percent of the product-level volatility, on average. This observation suggests a high level of asynchronicity among the dispersion of different products.

The relatively low number of observations per product groups can raise the potential concern of a small-sample bias. To address these concerns, we confirm our findings using a second data set of detailed barcode supermarket prices with thousands of observations per category. The data is from the U.S. and is available over 2001-2011. The marketing company IRI collects it,¹⁵ and includes weekly observations of average prices for 31 food and healthcare product categories (for example, carbonated beverages) sold in significant supermarkets all across the US (Bronnenberg, Kruger and Mela, 2008). The data set is unusually large, it includes over 200 million observations yearly of more than 150 thousand different products in 7900 stores.

We restrict attention to three major markets: New York, Chicago and Los Angeles.¹⁶ As before, we calculate weighted standard deviations of price changes across product categories and the whole cross section using yearly revenue shares as weights. The size of the dataset ensures that we have more than a thousand price change observations for each category each month, so the small-sample bias is minimal. We seasonally adjust and detrend the data.¹⁷

Figure D1 shows the weighted standard deviations of the price changes across the whole cross-section and three product categories of beer, carbonated beverages, and coffee. The figure shows that the dispersion is variable and is asynchronous across product categories. The cross-sectional standard deviation explains 8.7 percent of the 29 category level standard deviations, on average. This number is higher than the value we have obtained using the Hungarian CPI, but its low value is consistent with our observation that product-level price-change volatility is predominantly driven

¹²We use the consumption share of each product groups in the consumption expenditure survey as weights.

¹³We are using 3-digit product categories instead of 5-digit categories because it allows us to raise the number of observations within each category to minimize the small-sample bias. On average, we have 68 prices per category each month.

¹⁴We seasonally adjust the data using monthly dummies, and filter out the immediate impact of value-added tax changes by subtracting the coefficients of time-dummies that take the value 1 in the months with the tax changes. We obtain the cyclical component of the series by subtracting a Hodrick-Prescott trend from the series with a smoothing parameter of 129400.

¹⁵We would like to thank IRI for making the data available. All estimates and analysis in this paper, based on data provided by IRI, are by the authors and not by IRI.

¹⁶We make some straightforward adjustments to the data. First, we round prices toward the nearest penny, as fractional prices reflect the impact of promotional sales during the week, not actual price changes. Second, we winsorize price changes at ± 1 log points to minimize the impact of outliers. Third, we impute prices forward unchanged over a spell of missing observations, if the spells are no longer than one month and the prices before and after the spell are the same. Fourth, we only consider products that are available in the whole calendar year of the observation. Fifth, we sales-filter the data by eliminating temporary V-shaped drops in prices that are reversed entirely within five weeks (Nakamura and Steinsson, 2008). To calculate monthly price-change dispersions, we pool weekly price changes within each month. Furthermore, we exclude two major product categories: photo and razors, for which we do not have data during the whole sample period. The photo category, for example, mainly included accessories to film development, which became obsolete with the distribution of the digital technology.

¹⁷We use monthly dummies for seasonal adjustment and obtain the cyclical component of the series by subtracting a Hodrick-Prescott trend from the series with a smoothing parameter of 129400.

by idiosyncratic factors.

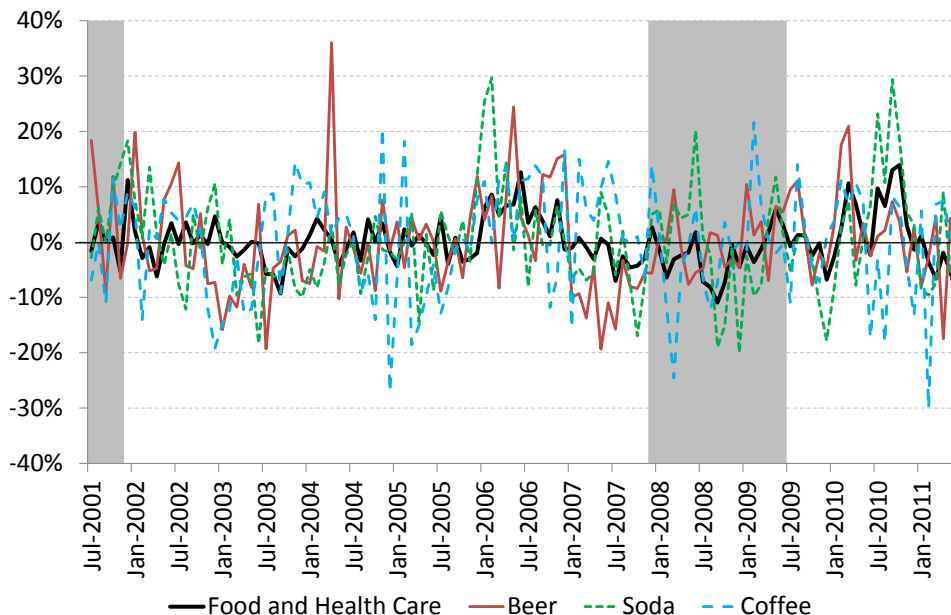


FIGURE D1. CYCLICAL VARIATION IN DISPERSION ACROSS GOODS

source: IRI Academic Dataset

Note: The figure shows the asynchronicity of the cyclical development of the product-level standard deviations of price changes between 2001-2011 among three example product categories and the whole cross section of food and health care products.

Finally, we show that aggregate price-change dispersion in U.S. CPI microdata also explains less than 10 percent of the *sectoral* price-change dispersions utilizing moments in Vavra (2014). To underpin the calculation of the monthly US consumer price index, the Bureau of Labor Statistics collects price quotes for thousands of goods and services across US retail establishments. Each product is assigned a fixed weight, which reflects its consumption share in the consumption expenditure survey. Using this data¹⁸, Vavra (2014) shows that the weighted cross-sectional standard deviation of log price changes ($dp_{it} = \log p_{it} - \log p_{it-1}$) varies countercyclically over his sample between January 1988 and January 2012 for the whole cross-section of price changes and also for most sectors. Figure D2 presents the cyclical development¹⁹ of this moment for the whole cross-section and three randomly chosen sectors of processed food, apparel and travel²⁰. As emphasized by Vavra (2014), the figure shows elevated aggregate standard deviations during each recession. The cyclical components of the standard deviations of the individual sectors are also positive, especially during the 2001 and 2007-2009 recessions. The figure also shows, however, that the cyclical behavior of the sectoral standard deviations is mostly asynchronous outside recessions. To measure the level of asynchronicity, we regress each sectoral standard deviation separately on the aggregate standard deviation and calculate the fraction of the sectoral time-series variation in dispersion that is explained by the aggregate, on average. We find that this average R^2 measure equals 9.7 percent in this sample. This means that aggregate volatility shocks explain only a small fraction of sectoral

¹⁸The data is using monthly price observations from New York, Chicago, Los Angeles; excludes price changes larger than 500 percent and smaller than 0.1 percent, sales-filtered and seasonally adjusted. Please see Vavra (2014) for details.

¹⁹The logarithm of standard deviation is filtered by using the Baxter-King (18,96,33) band-pass filter.

²⁰We thank Joseph Vavra for sharing his data.

volatility.

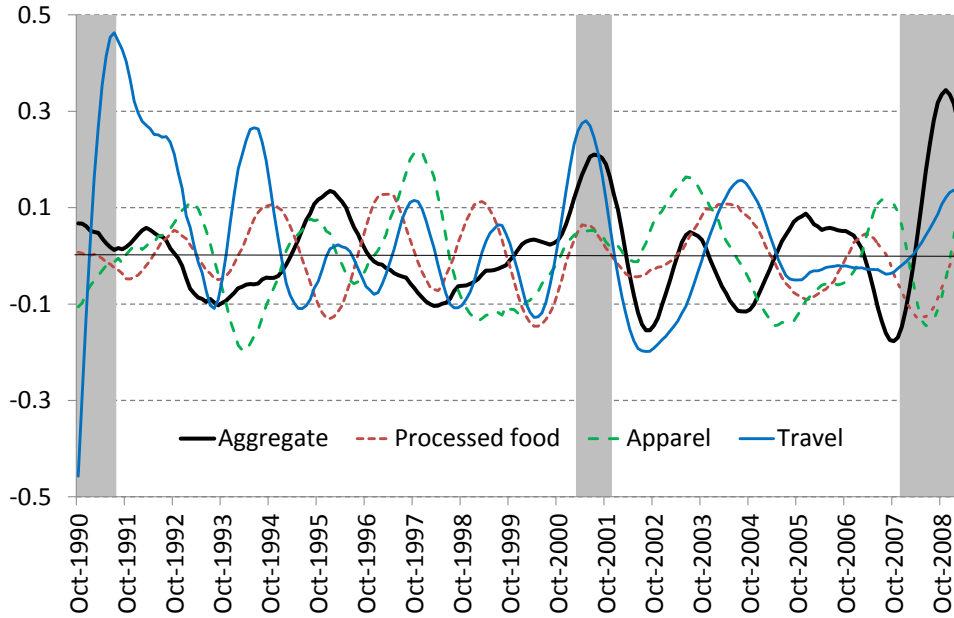


FIGURE D2. CYCLICAL VARIATION IN DISPERSION ACROSS US SECTORS

source: Vavra (2014)

Note: The figure shows the sectoral asynchronicity of the cyclical development of the weighted standard deviations of US CPI price changes between 1990-2009 among three example sectors and the whole consumption basket.

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