Sales are prevalent in retail
Yet, no role for sales in macro models

- Most macro models focus on “regular” prices
- Temporary price drops in the data are generally ignored

Figure 7: Peter Pan 18 ounce jar of Creamy Peanut Butter
Chevalier and Kashyap (2013)
Why ignore sales? Two main reasons

1. GE models: sales margin plays little role in the propagation of shocks to the real economy
   - Guimaraes and Sheedy (2011)
     - Price discrimination within standard macro model
     - Find that sales play no role
   - Kehoe and Midrigan (2012)
     - Lower menu cost of changing temporary price
     - Response to monetary shock mostly unchanged

2. Sales thought to be orthogonal to business cycle
   - Coibion et al. (2014), Anderson et al. (2014)
   - Exception: Sudo, Ueda, Watanabe and Watanabe (2014)
What We Do

- We revisit the role of sales for business cycles
  - Main message on ignoring sales in macro: “Not so fast!”

A ) Empirical contribution: cyclical nature of sales
  - Aggregate evidence using CPI data for U.K. and U.S.
  - Frequency of sales is highly countercyclical
  - Very robust result

B ) Theoretical contribution: GE model with sales
  - Sales margin can have a large impact on the response of agg. prices and output
  - Elasticity of search intensity is central to the role of sales
U.K. CPI Dataset

- 1996:02–2013:03 (212 months), 13 regions
- Monthly price quotes for 510 items across 14,000 stores
- Information on expenditure weights, regions, retailer type, sale flag, substitution flag, etc.
- Exclude obs with substitutions, or products with ≤ 10 obs
- ≈ 17 million observations
Sale filters

1. Sale flag
   - Price has to be available to all consumers
   - Excludes “2nd item at 50%”, loyalty cards, coupons, etc.

2. V-shaped sales
   - Similar to Nakamura and Steinsson (2008); max 3 months
   - Sale if Posted Price < Regular Price

3. Reference price filter
   - Modal price within 7-month centered around observation
   - Adjustments made to make sure changes in reference prices correspond to actual price changes
   - Sale if Posted Price < Reference Price
Sales – size distribution

- Spikes at 10%, 20%, 25%, 33% and 50%

- V-shaped and reference price filters pick up many more small sales

- Distributions for sales ≥ 10% very similar across filters
Basic moments – Sale prices

- When sales size ≥ 10%, moments are much more similar
- Av. sales frequency ≈ 2% (2 to 5% in Europe, 7 to 11% in U.S.)
- Av. size of sales ≈ 20–26%

<table>
<thead>
<tr>
<th></th>
<th>Sales flag</th>
<th>Sales flag (raw)</th>
<th>V-shaped</th>
<th>Reference price</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sales of at least 10%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>2.1%</td>
<td>2.7%</td>
<td>2.0%</td>
<td>2.5%</td>
</tr>
<tr>
<td>Mean size</td>
<td>-26.1%</td>
<td>-27.7%</td>
<td>-23.9%</td>
<td>-23.0%</td>
</tr>
<tr>
<td>Median size</td>
<td>-22.2%</td>
<td>-24.9%</td>
<td>-20.1%</td>
<td>-20.0%</td>
</tr>
</tbody>
</table>

Do firms adjust sales frequency over the business cycle?
Cyclical behaviour of sales in U.K.

- Compute fraction of items on sale in each month using CPI weights.
- Plot against indicator of the cycle: unemployment rate.
Regression analysis

- 5 p.p. rise in unemployment ≈ 2 p.p. more sales

- Relationship strongly significant

- Robust to:
  - Using different sales filters
  - Including trend, lags
  - Using other macroeconomic indicators
  - Including frequency of regular price changes
Not driven by a few categories

- Regress sales freq on detrended quarterly consumption data
- Out of 39 categories
  - ...25 have a negative and significant coeff. on real consumption
    - Most sensitive categories: Appliances, Spirits and A-V Equipment
  - ...2 have a positive and significant coefficient (Med. products, Books)
Not driven by a few categories

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- Similar results with fixed effects panel regressions at the product level

- However:
  - No relationship between sales freq. and unemp. across regions
    - National pricing?
  - No significant cyclicality of the size of sales
Evidence for the U.S.

- Restricted access to the CPI micro price data
  - No study looking specifically at the cyclicality of sales
  - Nakamura and Steinsson (2008): show upward trend in sales for select categories

- Information from two sources
  - Bureau of Labor Statistics compiled for us aggregate sales frequency from 2000
  - Vavra (2014)
    - Filters out sales and product substitutions for his analysis
    - Made available to us the residual series from 1988

*Do sales rise in slumps like in the U.K.?*
US sales frequency – BLS and Vavra (2014)
Reconciliation with CGH

- Coibion, Gorodnichenko and Hong (2014)
  - Find sales are mostly acyclical
  - IRI scanner dataset: grocery stores in 50 U.S. markets

- Do *Food* products behave differently?
From empirics to theory

- **Main empirical findings**
  - Frequency of sales is highly countercyclical in the UK and US

- **Do sales matter for macroeconomic models?**
  - Introducing sales makes no significant difference to IRFs
  - But model prediction of acyclical sales frequency is at odds with our findings

- Next: GE model with time-varying sales frequency...
  - ...but first, a little bit of intuition
Why could sales matter quantitatively?

- Aggregate price level in a CES framework with $\gamma_t$ sale prices and $1-\gamma_t$ regular prices:

$$P_t = \left[ \sum \left( \gamma_t \left( \delta P^R \right)^{1-\theta} + (1 - \gamma_t) \left( P^R \right)^{1-\theta} \right) \right]^\frac{1}{1-\theta}$$

- Log-linearized

$$\hat{P}_t \approx -\frac{1}{\theta - 1} \left( \delta^{1-\theta} - 1 \right) \tilde{\gamma}_t$$

- Impact of time-varying sales frequency is directly related to size ($\delta$) and elasticity of substitution ($\theta$)
Why could sales matter quantitatively?

\[ \hat{P}_t \approx -\frac{1}{\theta - 1} \left( \delta^{1-\theta} - 1 \right) \tilde{\gamma}_t \]

Sales can matter because...

1. ...they are large (\(\delta\) is low)...
   - 25% on average

1. ...they are very popular (\(\theta\) is large)
   - Glandon (2011): 15% items on sale = 40% of revenue

- CPI does not take #2 into account
  - Implicitly: \(\theta = 0\)

- One more channel? Sales more popular in recessions
  - Nevo and Wong (2015), Aguiar et al. (2012)
Empirical exercise: price gaps

- For each item/month, compute price gap from regular price: \( \ln(\frac{p^{\text{posted}}}{p^{\text{reg}}}) \)

- Make weight proportional to price gap, CES style
  \[ \omega = \left( \frac{p^{\text{posted}}}{p^{\text{reg}}} \right)^{-\theta} \]

- Example with 20% sale
  - \( \theta = 3 \): weight of 1.95
  - \( \theta = 5 \): weight of 3.05

- Aggregate across all items
  - Measures impact of sales on “regular” price index
  - Can compare to fixed-weight price index \((\theta = 0)\)
Impact of sales

\[ \theta = 0 \text{ (green)}, \ 3 \text{ (red)} \text{ or } 5 \text{ (blue)} \]
G.E. model with sales

Core: Model with differentiated varieties
► Each variety is produced by a monopolistically competitive firm
► Each household consumes some amount of every variety

Three modifications:

1. Household consists of continuum of household members
   ► Each member is responsible for purchasing a specific variety

2. Many brands for each variety; each retailer chooses
   ► Regular and sale price
   ► Fraction of brands at sale price

3. Many isolated locations
   ► Retailers compete for consumers
Household’s shopping choice

► Each household member...
  ► ...is responsible for buying a designated variety;
  ► ...can be either a **Bargain hunter** or a **Worker**.

1. **Worker**
  ► Earns labor income
  ► Picks a brand in random location

2. **Bargain hunter**
  ► Pays fixed random search cost in terms of lost labor income
  ► Buys designated variety in home location
  ► Faces higher probability of finding sale price
Model simulation

- 12-month staggered price contracts for regular price

A. Calibrated Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta )</td>
<td>5</td>
</tr>
<tr>
<td>( \varepsilon )</td>
<td>1</td>
</tr>
<tr>
<td>( \kappa )</td>
<td>0.08</td>
</tr>
<tr>
<td>( z_{max} )</td>
<td>0.31</td>
</tr>
</tbody>
</table>

* - in units of time

B. Targets (steady state)

<table>
<thead>
<tr>
<th>Target</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Markup</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>Price discount</td>
<td>0.78</td>
<td>0.78</td>
</tr>
<tr>
<td>Fraction of discounts</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>( \Delta ) Revenue share of sales from ( \Delta y=1)ppt</td>
<td>2.7</td>
<td>2.7</td>
</tr>
</tbody>
</table>

- Study responses to negative 1% impulse to money growth
  - Compare to responses in standard Taylor sticky-price model
Responses to a negative 1% impulse to money growth
Responses to a negative 1% impulse to money growth
What is behind the strong price response?

1. Discount is large, so small change in freq. of sales has large impact
What is behind the strong price response?

1. Discount is large, so small change in freq. of sales has large impact

2. “True CPI”: large weight on discounted items
   - Glandon (2011): 17% of items on sale = 40% of total revenue
   - Official CPI does not capture this dimension

**Takeaway**: With counter-cyclical sales, official CPI underestimates volatility of true price level
Conclusion

► **Our message:** we should not just ignore sales

1. Empirics: countercyclical frequency of sales
   ▶ True for U.K. and U.S.
   ▶ Very robust

2. Theory: model w/ search shows role for sales
   ▶ Significant impact on P in response to money shock
   ▶ Sales matter because of important weight in “true” CPI
   ▶ In addition: elastic customer search
     - Unemployed spend more time shopping than employed (Kruger-Muller, 2010; Kaplan-Menzio, 2013)
     - Aguiar, Hurst, Karabarbounis (2012): increase in time spent shopping during the Great Recession
     - Nevo and Wong (2015): buy more on sale, w/ coupons, etc.
Understanding IRFs

What is driving the model responses?

► Fraction of sales $\gamma_t$:
  - Markups rise because of sticky regular prices and falling mc
  - Firms want to attract more customers, now more valuable
  - Firms use sales to do so

► Also: more bargain hunters
  - More sales makes bargain hunting more interesting
  - Opportunity cost of search is lower (fall in wages)