Misinformed or mismatched?
Decomposing the gap between expected and realized wages among graduates in Mozambique

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UNU-WIDER, Mozambique

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1 Introduction

2 Framework

3 Background + Data

4 Results

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(1) Introduction
Motivation

- Systematically biased future expectations encountered in many settings
  - Labour market: expected wages > realized wages

- Pertinent since human capital investments made on basis of expected returns (Becker, 1964) : erroneous expectations $\implies$ resource misallocation
- Not so clear why positive bias (‘unrealistic optimism’) arises or persists
- We address this gap, using the structure of elicited expectations to identify proximate sources (types) of error
- Novel decomposition, using longitudinal data $\implies$ which types of errors matter
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Where might expectational errors come from?

In theory, 4 main types of error:

1. Over-confidence, ‘self-enhancement’ bias
2. Incomplete information regarding returns in labour market
3. Incomplete information regarding returns to individual characteristics
4. Mismatch into labour market positions:
   - Vertical: required vs actual education
   - Horizontal: field of study vs field of work
   - Temporal: time to complete studies

Important since mismatches typically associated with material wage penalties (McGuinness et al., 2018; Somers et al., 2019)

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(2) Framework
Starting point: (subjective) own-wage expectations are almost always of a **conditional** form:

\[ w_{ij}^e = E(w_{ij} | O^e, \Omega^e) \]

i.e., expectations are conditional on outcomes (the desired job) and perceived rewards to these same same outcomes.

To put empirical structure on this, use a Mincerian (hedonic) wage function:

\[
W_{ijt} = e^{\mu + \delta t} Z_{it}^\beta H_{jt}^\gamma \epsilon_{it} \\
\ln W_{ijt} = w_{ijt} = \mu + \delta t + z_{it}^\beta h_{jt}^\gamma + \epsilon_{it} \\
\Rightarrow w_{ijt}^e = \mu^e + \delta^e t_{ij}^e + z_{it}^e \beta^e + h_{jt}^e \gamma^e + \epsilon_{ij}^e
\]

So, this means we have:

\[
\Omega^e = \{\mu^e, \delta^e, \beta^e, \gamma^e\}; \quad O^e = \{t_{ij}^e, Z_{it}^e, H_{jt}^e\}
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**Expected rewards**; **Expected outcomes**
Proximate determinants of earnings

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Expected rewards \quad \quad \quad Expected outcomes
Expectational error decomposition

Comparing expected vs. realized wages gives the **expectational error**:

$$w_i^e - w_i^r = (\mu^e - \mu^r) + (t_i^e \delta^e - t_i^r \delta^r) + (z_i^e \beta^e - z_i^r \beta^r) + (h_j^e \gamma^e - h_j^r \gamma^r) + (\varepsilon_i^e - \varepsilon_i^r)$$

Overall error

Noting that: $z_i^e \beta^e - z_i^r \beta^r = z_i^e \Delta \beta + \Delta z_i^e \beta^r$ (c.f., Blinder-Oaxaca)

Gives the error decomposition:

$$\ln W_i^e - \ln W_i^r \equiv \Delta w_{it} = e_i^P + e_i^I + e_i^M + \Delta \varepsilon_{it}$$

$$e_i^P = \Delta \mu \quad (2a)$$

$$e_i^I = (t_i^e \Delta \delta + z_i^e \Delta \beta) + h_j^e \Delta \gamma \quad (2b)$$

$$e_i^M = \Delta t_i \delta^r + \Delta z_i \beta^r + \Delta H_j \gamma^r \quad (2c)$$
Four sources / types of error

1. $e^P_i$: **generic optimism** (c.f., macro., optimism as shocks to TFP)

2. $e^{I(j)}_i$: information regarding rewards to job characteristics

3. $e^{I(i)}_i$: information regarding rewards to individual characteristics

4. $e^M_i$: job match quality (outcomes)
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(3) Background + Data
Application to Mozambique

Relevant aspects of country context:

- Significant human capital deficit, reflecting legacy of colonialism and subsequent conflict

- Rapid growth of tertiary education over past decades (30% per year), from low base:
  - 700 new graduates in 2003 → 18,000 in 2016

- Challenging jobs environment:
  - 300,000 young people entering labour market each year
  - only 12% of all workers earn a wage
  - current real GDP growth barely matches population growth
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Baseline survey in 2017 of final year undergraduates in 6 major universities in the country, public and private

Sample representative by university, study area and gender

Initial sample = 2,176 students, of which 1,989 provided valid wage expectations information

2018–2019, 4 waves of follow-up via mobile phone (2 further waves planned) => here we cover 12 months post-study

Low attrition: 1,887 followed-up at least one (5.1% lost/refused)

Focus here on value of *first wage* reported during post-study follow-up period vs. expected first wage reported at baseline
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<th>Obtained work post-study?</th>
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<th>All</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>24.42</td>
<td>26.93</td>
<td>26.05</td>
</tr>
<tr>
<td>Age</td>
<td>(0.17)</td>
<td>(0.20)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>Female</td>
<td>0.60</td>
<td>0.36</td>
<td>0.44</td>
</tr>
<tr>
<td>Married</td>
<td>0.09</td>
<td>0.18</td>
<td>0.14</td>
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<tr>
<td>Has kids</td>
<td>0.20</td>
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<td>Public university</td>
<td>0.71</td>
<td>0.85</td>
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<td>73.68</td>
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</tr>
<tr>
<td>Humanities</td>
<td>0.01</td>
<td>0.02</td>
<td>0.02</td>
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<tr>
<td>Social Sciences</td>
<td>0.51</td>
<td>0.40</td>
<td>0.44</td>
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<td>Natural Sciences</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>Engineering</td>
<td>0.07</td>
<td>0.08</td>
<td>0.07</td>
</tr>
<tr>
<td>Agriculture</td>
<td>0.05</td>
<td>0.06</td>
<td>0.05</td>
</tr>
<tr>
<td>Health</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Observations            | 700    | 1,187  | 1,887  |
Realized outcomes in first paid position (N = 1,887)

<table>
<thead>
<tr>
<th>Private sector employee</th>
<th>Male</th>
<th>Female</th>
<th>Public sector employee</th>
<th>Male</th>
<th>Female</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private uni.</td>
<td>0.57</td>
<td>0.62</td>
<td>Public uni.</td>
<td>0.42</td>
<td>0.46</td>
<td>0.46</td>
</tr>
<tr>
<td>Public uni.</td>
<td>0.21</td>
<td>0.12</td>
<td>Public uni.</td>
<td>0.27</td>
<td>0.33</td>
<td>0.27</td>
</tr>
<tr>
<td>NGO employee</td>
<td>0.07</td>
<td>0.04</td>
<td>NGO employee</td>
<td>0.09</td>
<td>0.05</td>
<td>0.07</td>
</tr>
<tr>
<td>Self employed</td>
<td>0.11</td>
<td>0.16</td>
<td>Self employed</td>
<td>0.19</td>
<td>0.14</td>
<td>0.17</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Study unfinished</th>
<th>Male</th>
<th>Female</th>
<th>Male</th>
<th>Female</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private uni.</td>
<td>0.79</td>
<td>0.78</td>
<td>Public uni.</td>
<td>0.86</td>
<td>0.82</td>
</tr>
<tr>
<td>Public uni.</td>
<td>0.55</td>
<td>0.63</td>
<td>Public uni.</td>
<td>0.50</td>
<td>0.57</td>
</tr>
<tr>
<td>NGO employee</td>
<td>0.13</td>
<td>0.18</td>
<td>NGO employee</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>Self employed</td>
<td>0.43</td>
<td>0.38</td>
<td>Self employed</td>
<td>0.48</td>
<td>0.38</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Works part time</th>
<th>Male</th>
<th>Female</th>
<th>Male</th>
<th>Female</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private uni.</td>
<td>0.73</td>
<td>0.66</td>
<td>Public uni.</td>
<td>0.74</td>
<td>0.71</td>
</tr>
<tr>
<td>Public uni.</td>
<td>0.69</td>
<td>0.63</td>
<td>Public uni.</td>
<td>0.68</td>
<td>0.58</td>
</tr>
<tr>
<td>NGO employee</td>
<td>0.62</td>
<td>0.67</td>
<td>NGO employee</td>
<td>0.68</td>
<td>0.60</td>
</tr>
<tr>
<td>Self employed</td>
<td>0.41</td>
<td>0.39</td>
<td>Self employed</td>
<td>0.52</td>
<td>0.44</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mismatch count</th>
<th>Private uni.</th>
<th>Public uni.</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private uni.</td>
<td>3.88</td>
<td>4.02</td>
<td>3.98</td>
</tr>
<tr>
<td>Public uni.</td>
<td>4.09</td>
<td>3.79</td>
<td>3.98</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Realized wage (USD/month)</th>
<th>Private uni.</th>
<th>Public uni.</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private uni.</td>
<td>226.23</td>
<td>196.23</td>
<td>149.85</td>
</tr>
<tr>
<td>Public uni.</td>
<td>149.85</td>
<td>139.17</td>
<td>156.21</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Expected - realized wage (USD)</th>
<th>Private uni.</th>
<th>Public uni.</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private uni.</td>
<td>255.31</td>
<td>228.51</td>
<td>293.60</td>
</tr>
<tr>
<td>Public uni.</td>
<td>239.67</td>
<td>270.37</td>
<td>239.67</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Expectational error (log.)</th>
<th>Private uni.</th>
<th>Public uni.</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private uni.</td>
<td>0.94</td>
<td>0.92</td>
<td>1.27</td>
</tr>
<tr>
<td>Public uni.</td>
<td>1.13</td>
<td>1.11</td>
<td>1.18</td>
</tr>
</tbody>
</table>
Expected vs. realized wages

Cross-sectional differences

![Graph showing expected vs. realized wages](image-url)
Expected vs. realized wages

Individual-level errors

Cumulative probability vs. Expected - realized wage (USD)
Expected vs. realized wages

Individual-level errors

Cumulative probability

Ratio of error / realized wage
(4) Results
Results

- Levels regression: Determinants of wages
- Error regression: Error decomposition
- Decomposition: Error components
- Figure 1: Mean error components
- Figure 2: Error component distributions
- Figure 3a: Subcomponents job chars. error
- Figure 3b: Subcomponents indiv chars. error
- Figure 3c: Subcomponents match quality error
- Figure 4: Errors by mismatch count
- Figure 5: Errors by quantile of expectational errors
<table>
<thead>
<tr>
<th></th>
<th>(I) Job?</th>
<th>(II) Expected wage</th>
<th>(III) Realized wage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
<td>0.71***</td>
<td>3.17***</td>
<td>3.17***</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.15)</td>
<td>(0.17)</td>
</tr>
<tr>
<td><strong>Female</strong></td>
<td>-0.18***</td>
<td>-0.15***</td>
<td>-0.07</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.06)</td>
</tr>
<tr>
<td><strong>Private university</strong></td>
<td>-0.14***</td>
<td>0.04</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.05)</td>
<td>(0.08)</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td>0.02</td>
<td>-0.03</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td><strong>Engineering</strong></td>
<td>0.02</td>
<td>0.22**</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.09)</td>
<td>(0.12)</td>
</tr>
<tr>
<td><strong>Academic level (self)</strong></td>
<td>0.05*</td>
<td>0.03</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.04)</td>
</tr>
<tr>
<td><strong>Public employee</strong></td>
<td>-0.01</td>
<td>-0.05*</td>
<td>-0.04</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.04)</td>
</tr>
<tr>
<td><strong>Self employed</strong></td>
<td>0.01</td>
<td>-0.02</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td><strong>Nonselection hazard</strong></td>
<td>-0.11*</td>
<td></td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Study unfinished</strong></td>
<td></td>
<td></td>
<td>-0.28***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.07)</td>
</tr>
<tr>
<td><strong>Works part time</strong></td>
<td></td>
<td></td>
<td>-0.32***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.06)</td>
</tr>
<tr>
<td><strong>Job unlike course</strong></td>
<td></td>
<td></td>
<td>-0.17***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.05)</td>
</tr>
</tbody>
</table>

**Obs.**                  | 1,887    | 1,887              | 1,187              |
**R^2**                   | 0.20     | 0.14               | 0.15               |

Actual outcomes? No No No No No Yes
<table>
<thead>
<tr>
<th></th>
<th>(I) OLS</th>
<th>(II) Robust</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>1.52***</td>
<td>1.61***</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>Female</td>
<td>-0.24***</td>
<td>-0.21***</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Prev. work exp.</td>
<td>0.03***</td>
<td>0.03***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Private university</td>
<td>-0.35***</td>
<td>-0.34***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.08)</td>
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<tr>
<td>Health</td>
<td>0.33***</td>
<td>0.35***</td>
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<td></td>
<td>(0.11)</td>
<td>(0.13)</td>
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<tr>
<td>Academic level (self)</td>
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<td>-0.12***</td>
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<tr>
<td></td>
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<td>(0.05)</td>
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<td>Self employed</td>
<td>0.09</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Study unfinished (Δ)</td>
<td>-0.23***</td>
<td>-0.24***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Works part time (Δ)</td>
<td>-0.35***</td>
<td>-0.37***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Job unlike course (Δ)</td>
<td>-0.13***</td>
<td>-0.18***</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>NGO employee (Δ)</td>
<td>0.21**</td>
<td>0.28***</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Self employed (Δ)</td>
<td>-0.29***</td>
<td>-0.22***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Obs.</td>
<td>1,187</td>
<td>1,187</td>
</tr>
<tr>
<td>R²</td>
<td>0.14</td>
<td>0.24</td>
</tr>
</tbody>
</table>
Error components

Combine terms, using a shrinkage approach – e.g.,:

\[ \hat{e}_i^M = \sum_{x \in \Delta t, \Delta Z, \Delta H} x_i \times \hat{\theta}_x \times [1 - Pr(\hat{\theta}_x = 0)] \]  

\[ (3) \]

<table>
<thead>
<tr>
<th></th>
<th>(I) OLS</th>
<th>(II) Robust</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimism</td>
<td>1.52</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>[1.2,1.9]</td>
<td>[0.3,1.3]</td>
</tr>
<tr>
<td>Job info.</td>
<td>0.11</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>[0.0,0.2]</td>
<td>[-0.0,0.3]</td>
</tr>
<tr>
<td>Indiv. info.</td>
<td>-0.40</td>
<td>-0.25</td>
</tr>
<tr>
<td></td>
<td>[-0.5,-0.2]</td>
<td>[-0.4,-0.1]</td>
</tr>
<tr>
<td>Match quality</td>
<td>0.00</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>[..,]</td>
<td>[0.4,0.7]</td>
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</tbody>
</table>
Mean error components

- Match quality (0.54)
- Indiv. info. (-0.30)
- Job info. (0.07)
- Optimism (0.87)
Error component distributions

-1 -0.5 0 0.5 1 1.5

-1 -0.5 0 0.5 1 1.5

Job info. (0.07)  Indiv. info. (-0.30)  Match quality (0.54)
Subcomponents of job info. error

- Private services: -0.02
- Secondary sector: -0.01
- Edu/health services: 0.03
- Self employed: 0.04
- Public employee: 0.04

Total error = 0.07
Subcomponents of individual info. error

Contribution

English proficiency
Academic level (self)
Family public sector
Has kids
Prev. internship

Total error = -0.30
Subcomponents of match quality error

- Intern position: 0.04
- Searching for work: 0.05
- Job unlike course: 0.10
- Works part time: 0.16
- Study unfinished: 0.20

Total error = 0.54
Errors by quantile of expectational errors

- Optimism
- Jobs info.
- Indiv.info.
- Match quality
(5) Summary
Summary

Contributions:
1. Go beyond aggregate errors to shed light on relevant types (sources) of error
2. Practical decomposition leveraging the conditional structure of expected wages
3. First longitudinal study of expectational errors among graduates in low income country (Mozambique)

Highlights:
1. Overall, expectational errors are very large (> 100%)
2. Specific informational errors not so important, even negative w.r.t. indiv. chars
3. Errors due to job mismatch are large and prevalent, accounting for \(\approx 50\%\) of expectational error in first wage in post-study period
4. Generic optimism (productivity) is also substantial, much larger than elsewhere
Summary

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4. Generic optimism (productivity) is also substantial, much larger than elsewhere
Summary

Finally, some broader implications:

1. **Key challenge is to further understand and (perhaps) address mismatches, which are indicative of significant market frictions & demand-side constraints**
   - Students have some info. about labour market rewards ...
   - But less capacity to navigate opportunities and secure ‘good’ job posts

2. **Magnitude of generic optimism may be a cause for concern (e.g., potential source of youth frustration), but difficult to interpret per se**
   - Does not appear to be *only* self-enhancement bias
   - Perhaps reflects continuation of economic crisis (in part)

3. **Future work on how expectations are formed is necessary (i.e., are expectations updated based on new info.?)**
Finally, some broader implications:

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   – Students have some info. about labour market rewards ...
   – But less capacity to navigate opportunities and secure ‘good’ job posts

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   - But less capacity to navigate opportunities and secure ‘good’ job posts

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   - But less capacity to navigate opportunities and secure ‘good’ job posts

2. Magnitude of generic optimism may be a cause for concern (e.g., potential source of youth frustration), but difficult to interpret per se
   - Does not appear to be only self-enhancement bias
   - Perhaps reflects continuation of economic crisis (in part)

3. Future work on how expectations are formed is necessary (i.e., are expectations updated based on new info.?)