# Liquidity Constraints and Mortality in Brazil

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# Literature

- **Stephens (AER, 2003)**:
  - Presents evidence that goes against the life cycle/permanent income theories (individuals smoothing consumption throughout life);
  - Studies the effect of a **permanent and predictable** income shock: retirement checks from the US Social Security Administration, paid in the 3rd of the month;
  - Finds a temporary increase w.r.t the mean (7 to 20%) in the consumption patterns of various categories;
- **Evans & Moore (REStat, 2012)**
  - Find an intra-month mortality cycle in the U.S: deaths increase after the 1st of the month (usual payday) and fall in the days just before;
  - More pronounced in causes more intimately related to the level of economic activity: traffic accidents, cardiac diseases, stroke etc. Nonexistent for unrelated causes such as cancer, COPD, etc.
  - Argue that the lack of liquidity in certain periods of the month decreases mortality, which in turn increases when this lack of liquidity is eased by receiving income.

# Literature

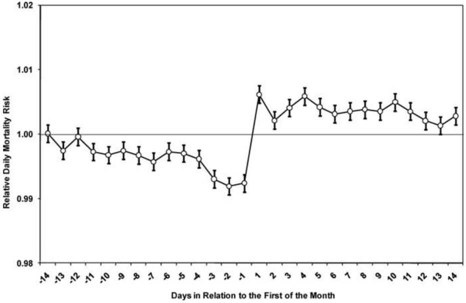



Figure: Evans & Moore (2012)

- **Phillips et al., 1999**:
  "Money for purchasing drugs or alcohol tends to be available at the beginning of the month and is relatively less available at the end of the month".

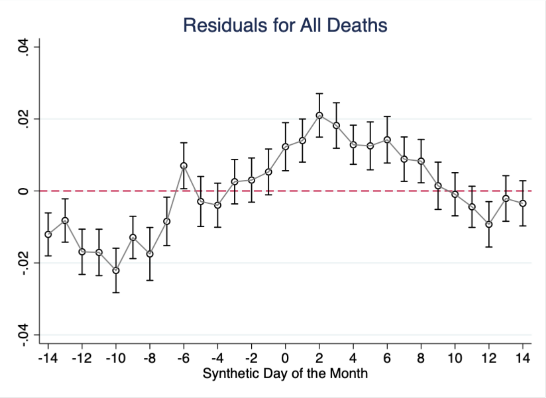
# Mortality Cycle - SIM/DATASUS

- Microdata on mortality from SIM/DATASUS, 2001 to 2018;
- Filtered to include only men aged 18-60 years old $\rightarrow$ more likely to be working;
- Brazilian law: payment must be made **until** the 5th business day of the month;
- Variable:
  $Synth.\ Day\ of\ Death = Date\ of\ death - Date\ of\ the\ 5th\ business\ day$.
- Selected deaths occurring within a 14-day window around payday (5th biz day): variable ranges from -14 to +14.
- Because the 5th business day occurs mostly on Fridays (3/7 of times), we regress:

$$ln(Deaths_t) = \beta_0 + \beta_1 Holiday_t + \sum_{j=1}^{7} Weekday_{jt} + \sum_{k=1}^{12} Month_{kt} \times Year_t + \epsilon_{it}$$

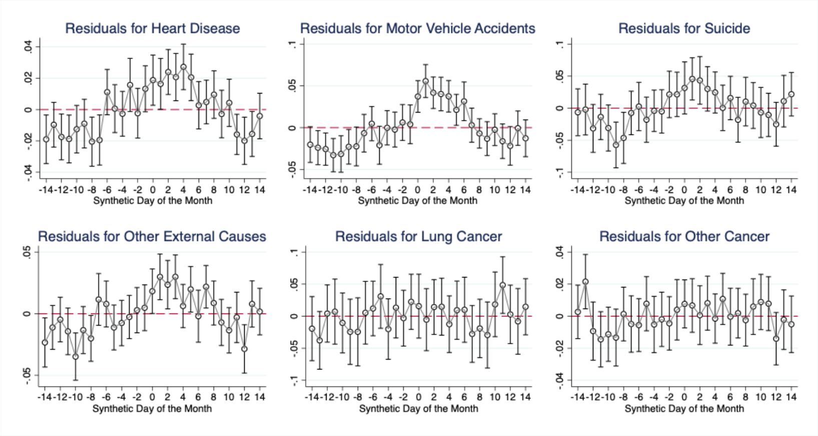
- Plot the average residuals by selected causes of death in each synth. day.

# Mortality Cycle - Results




- Mortality increases in the 6 days following payday, with a reversion to the predicted by the regression after this period.
- Fall in the days $< -6$, and zero in $[-6, -1]$, which makes sense since some workers are paid before the 5th biz. day of the month.

# Mortality Cycle - Causes of Death




- Effect more pronounced in causes more intimately related to the level of economic activity (accidents, heart disease, suicide).
- Nonexistent for cancers.

# Mortality Cycle

- Suggestive evidence on the impact of income receipt and mortality;
- But susceptible to confounders: there may be other reasons for the existence of this cycle (e.g: misreported dates of deaths, bills due, etc.);
- We'll use a natural experiment, the Abono Salarial program, to obtain clearer and cleaner evidence.

# The "Abono Salarial" Program

- Positive temporary income shock: 1 minimum wage per year, paid according to the **month of birth** of the worker, usually not in the beginning of the month;
- **Eligibility:** Average monthly income $\leq$ 2 minimum wages + worked at least 30 days + being enrolled in the PIS for at least 5 years, in the reference year.
- **RAIS dataset:** identified matched employer-employee data reported by employers to the Ministry of Labor, on a yearly basis.
  - Information on salary, tenure, age, date of birth, etc. of workers;
  - Information on the exact date and reason for termination of employment: retirement, firing, **death**, etc.
  - Period selected: 2014 to 2017 (reference years 2013-2016);
  - We are able to recover the average monthly income, duration of employment spell and date of death for each CPF (personal identifier).
- We focus on the mortality effects of receiving such extra income.

# The "Abono Salarial" Program

| Year: | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|
| **Month of Birth** | **Paid from** | | | |
| July | 15/Jul/14 | 22/Jul/15 | 28/Jul/16 | 27/Jul/17 |
| August | 22/Jul/14 | 20/Aug/15 | 18/Aug/16 | 17/Aug/17 |
| September | 31/Jul/14 | 17/Sep/15 | 15/Sep/16 | 14/Sep/17 |
| October | 14/Aug/14 | 15/Oct/15 | 14/Oct/16 | 19/Oct/17 |
| November | 21/Aug/14 | 19/Nov/15 | 21/Nov/16 | 17/Nov/17 |
| December | 28/Aug/14 | 17/Dec/15 | 15/Dec/16 | 14/Dec/17 |
| January | 16/Sep/14 | 14/Jan/16 | 19/Jan/17 | 18/Jan/18 |
| February | 23/Sep/14 | 14/Jan/16 | 19/Jan/17 | 18/Jan/18 |
| March | 30/Sep/14 | 16/Feb/16 | 16/Feb/17 | 22/Feb/18 |
| April | 14/Oct/14 | 16/Feb/16 | 16/Feb/17 | 22/Feb/18 |
| May | 21/Oct/14 | 17/Mar/16 | 16/Mar/17 | 15/Mar/18 |
| June | 31/Oct/14 | 17/Mar/16 | 16/Mar/17 | 15/Mar/18 |
| Value of MW in t(-1) | R$678 | R$724 | R$788 | R$880 |
| Max. AS amount | R$724 | R$788 | R$880 | R$937 |

- Usually at the end of the month;
- 2015-2017: happens in the worker's birthday month;
- December: confounds with second installment of *13º salário*.

# Empirical Strategy

- Group by week: 48 weeks in each year (4 weeks/month, last week with 7-10 days) $\rightarrow$ 192 weeks across all 4 years;
- Month-of-birth groups: 24 groups, 12 being treated (income $\leq 2$ minimum wages) and 12 control ($2 <$ income $\leq 3$ min. wages);
- **Poisson** estimation of:

$$\text{Count of Deaths}_{gt} = \alpha_t + \gamma_g + \sum_{j=-1}^{+1} \beta_j \textit{Payweek}(j)_{gt} + \varepsilon_{gt}$$

- Where:
  - $\alpha_t$ represent week fixed-effects ($t \in \{1, 2, ..., 192\}$);
  - $\gamma_g$ represent month-of-birth-treated fixed effects ($g \in \{1, 2, ..., 24\}$);
  - $\textit{Payweek}(j)_{gt}$ is a dummy equal to 1 if group $g$ is treated is week $t + j$, with $j \in \{-1, 0, +1\}$
- Standard-errors clustered at the group level, p-values obtained by *Score Bootstrap* (Kline & Santos (2012)) due to the small number of clusters.
- Three estimations: non-eligible + not-yet-eligible as control, not-yet-eligible only as control, placebo with non-eligible only.

# Results - Full Sample

| Benchmark: | Non-eligible | Eligible | Placebo |
|---|---|---|---|
| | Deaths | Deaths | Deaths |
| Payweek(-1) | -0.0155 | -0.0319 | 0.0265 |
| | (0.0337) | (0.0376) | (0.0789) |
| | [0.6777] | [0.4184] | [0.7347] |
| Payweek | 0.0944*** | 0.0946*** | 0.0335 |
| | (0.0330) | (0.0336) | (0.0420) |
| | [0.0050] | [0.0080] | [0.4595] |
| Payweek(+1) | -0.0224 | -0.0284 | -0.0108 |
| | (0.0384) | (0.0425) | (0.0553) |
| | [0.6166] | [0.4955] | [0.8679] |
| Constant | 2.212*** | 3.115*** | 2.223*** |
| | (0.0601) | (0.0841) | (0.104) |
| | [0.0000] | [0.0000] | [0.0000] |
| Observations | 4603 | 2304 | 2299 |
| Mean Dep. Var. | 11.73 | 16.23 | 7.21 |

Standard errors clustered at the month of birth $\times$ treated level in parentheses.
Month of birth and week in year fixed effects included.
Score-bootstrapped p-values in brackets:
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

# Results - Full Sample

- $\approx 9.5\%$ increase in average number deaths in the week of payment when compared to other weeks;
- Average of outcome variable:
  - **Non-eligible:** $11.73 \rightarrow \approx 1.11$ extra deaths in payweek;
  - **Eligible:** $16.29 \rightarrow \approx 1.54$ extra deaths in payweek.

# Results - No December

- Notice that the payment in December confounds with receiving the secons installment of the "13º salário" (bonus paid to workers in Brazil, which must be deposited in two installments, the first one no later than the beginning of December, second one middle of December).
- This could create a compound effect that would be due to receiving half a months salary, and not the Abono Salarial per-se.
- Receiving half a salary close to the date of the Abono could distub the pattern of deaths in the neighbouring days;
- To deal with that, we excluded workers receiving their Abono Salarial in December.
- Results get even stronger.

# Results - No December

| Benchmark: | Non-eligible | Eligible | Placebo |
|---|---|---|---|
| | Deaths | Deaths | Deaths |
| Payweek(-1) | -0.0137 | -0.0372 | 0.0446 |
| | (0.0382) | (0.0395) | (0.0839) |
| | [0.7337] | [0.3754] | [0.6156] |
| Payweek | 0.108*** | 0.113*** | 0.0321 |
| | (0.0322) | (0.0312) | (0.0468) |
| | [0.0030] | [0.0030] | [0.5285] |
| Payweek(+1) | -0.0334 | -0.0386 | -0.0239 |
| | (0.0407) | (0.0427) | (0.0615) |
| | [0.4705] | [0.3664] | [0.7588] |
| Constant | 2.218*** | 3.044*** | 2.180*** |
| | (0.0613) | (0.0740) | (0.0990) |
| | [0.0000] | [0.0000] | [0.0000] |
| Observations | 4315 | 2160 | 2155 |
| Mean Dep. Var. | 11.69 | 16.17 | 7.20 |

Standard errors clustered at the month of birth $\times$ treated level in parentheses.
Month of birth and week in year fixed effects included.
Score-bootstrapped p-values in brackets:
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

# Results - Birthday Effect

- Notice that in the years of 2015-2017, payment is made in the month of birthday of the worker;
- This could confound our analysis: having a birthday may disrupt mortality patterns due to, for example, celebrating, mid-life crisis, etc.
- This effect could be different for lower or higher income workers, such that it could not be accounted for by using never-eligible workers as control;
- To deal with this, we restrict the sample to the year of 2014, in which payments did not follow workers' months of birth (except for July, which we drop from the sample).

# Results - Birthday Effect

| Benchmark: | Non-eligible | Eligible | Placebo |
|---|---|---|---|
| | Deaths | Deaths | Deaths |
| Payweek(-1) | 0.00489 | 0.0252 | -0.0388 |
| | (0.0622) | (0.0704) | (0.101) |
| | [0.9309] | [0.7427] | [0.6717] |
| Payweek | 0.140* | 0.148** | 0.0439 |
| | (0.0720) | (0.0603) | (0.131) |
| | [0.0641] | [0.0210] | [0.7457] |
| Payweek(+1) | -0.0540 | -0.0169 | -0.139 |
| | (0.0619) | (0.0829) | (0.159) |
| | [0.4204] | [0.8348] | [0.3684] |
| Constant | 2.191*** | 2.895*** | 2.056*** |
| | (0.0511) | (0.0601) | (0.0618) |
| | [0.0000] | [0.0000] | [0.0000] |
| Observations | 1056 | 528 | 528 |
| Mean Dep. Var. | 11.91 | 16.25 | 7.21 |

Standard errors clustered at the month of birth × treated level in parentheses.
Month of birth and week in year fixed effects included.
Score-bootstrapped p-values in brackets:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

- Results persist for this sample.

# Results - Causes of Death

- We were able to match employee mortality data with the SIM/DATASUS dataset via date of birth, month of death, gender and state;
- We present the result for aggregated causes of deaths following ICD-10 codes;
- For simplicity, we only present the $Payweek(0)$ coefficient (though our regressions are estimated the same way) and only with eventually eligible workers in the control group.

# Results - Causes of Death

| **Cause** | Malign Neoplasms | Infectious Diseases | Endocrin Diseases | Mental Disorders | Circulatory Disorders |
|---|---|---|---|---|---|
| Payweek | -0.00178 | 0.0791 | 0.188 | -0.104 | 0.138** |
| | (0.0733) | (0.0834) | (0.104) | (0.155) | (0.0566) |
| | [0.9850] | [0.3333] | [0.1301] | [0.5115] | [0.0490] |
| Mean Dep. Var. | 3.024 | 2.902 | 1.388 | 0.960 | 4.748 |
| % of Total Deaths | 19.11 | 18.12 | 8.73 | 5.74 | 29.09 |
| **Cause** | Respiratory Disorders | Digestive Disorders | Injury & Poisoning | External | Others |
| Payweek | -0.0180 | 0.125 | 0.0900 | 0.0939** | 0.246*** |
| | (0.0790) | (0.0874) | (0.0972) | (0.0453) | (0.0904) |
| | [0.8248] | [0.2202] | [0.3714] | [0.0490] | [0.0470] |
| Mean Dep. Var. | 3.809 | 1.566 | 2.658 | 7.889 | 2.401 |
| % of Total Deaths | 23.63 | 9.78 | 15.92 | 47.87 | 14.99 |

Standard errors clustered at the month of birth × treated level in parentheses.
Month of birth and week in year fixed effects included.
Score-bootstrapped p-values in brackets: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

- Results for circulatory disorders (heart attack, hearts disease, thrombosis etc.), external causes and other non-classified deaths;
- No effect for some causes that should not be affected by economic activity (cancers (malign neoplasms) and respiratory disorders).

# Results - Who drives?

- To check if there is heterogeneity between male and female workers, we re-estimated the second specification of our main results table for each gender;
- For simplicity, we only present the *Payweek*(0) coefficient (though our regressions are estimated the same way) and only with eventually eligible workers in the control group.

| | (1)<br>Male Deaths | (2)<br>Female Deaths |
|---|---|---|
| Payweek | 0.109*** | 0.106 |
| | (0.0357) | (0.0760) |
| | [0.0100] | [0.2222] |
| Observations | 2160 | 2141 |

Standard errors clustered at the month of birth $\times$ treated level in parentheses.
Month of birth and week in year fixed effects included.
Score-bootstrapped p-values in brackets:
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

- Male workers drive all the results: from now on, we'll focus on this subset of workers.

# Regression Discontinuity Design (RDD)

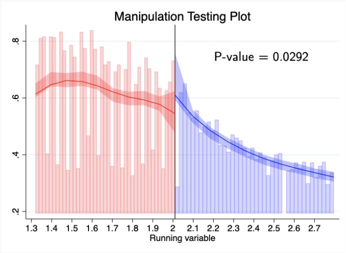
- Abono salarial is paid only to workers with an average monthly income less or equal to 2 minimum wages (MWs);
- Discontinuity in 2 MWs: if we restrict our sample to workers otherwise eligible (worked more than 30 days and are registered with PIS for at least 5 years), we get a RD design, because every worker in the sample receiving $\leq 2$ MWs is treated, $> 2$ MWs not treated;
- Allows us to estimate a regression in the individual level, stacking all years:

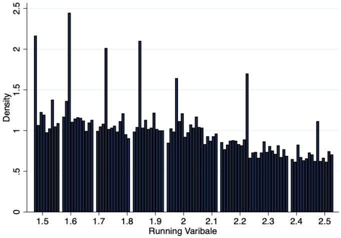
$$\text{Died}_i = f(MW_i) + \beta \mathbb{1}_{\{MW_i > 2\}} + \varepsilon_i$$

- Where:
  - *Died*$_i$ is a dummy variable equal to 1 if the individual died in the **15 days** following the date in which she was supposed to be paid;
  - $f(MW_i)$ is a polynomial function of $p^{th}$ order;
  - $\varepsilon_i$ is an error term.
- Our interest lays in the $\beta$ coefficient. Salary in MWs in our dataset varies at the 0.01 level. We only keep **male** workers.

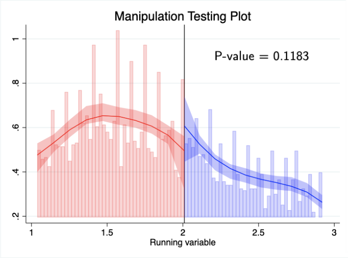
# Density Test and Heaping

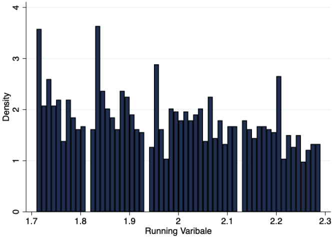
Panel A: All years




Panel B: 2014 only



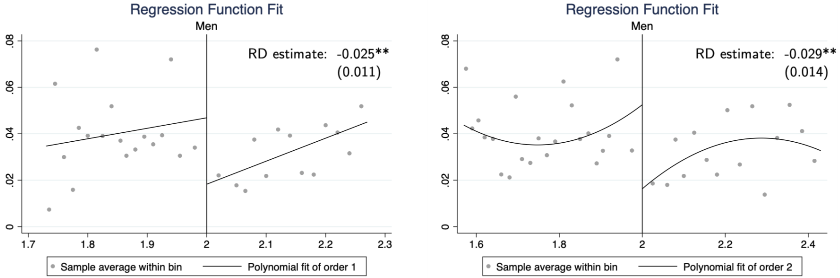
# Strategy and Results

- To account for heaping and possible manipulation, our estimates will exclude a vicinity around cutoff (Donut Hole RD): we exclude the interval $[1.98, 2.02]$;
- Bandwidths were selected with the *rdrobust* command.

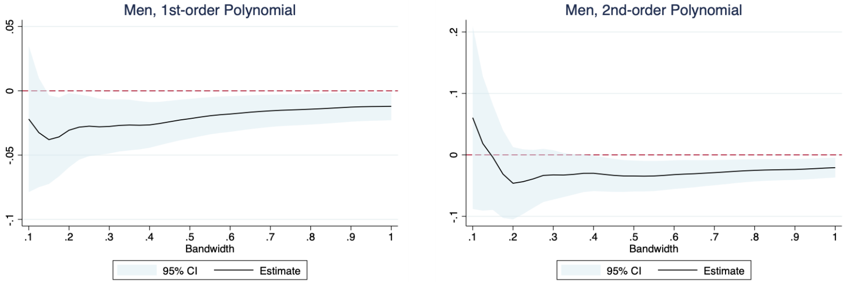
| | **Discontinuity** |
|---|---|
| **Panel A: No covariates** | |
| Linear | -0.031<br>(Robust p-value = 0.007)<br>BW = 0.247 |
| Quadratic | -0.034<br>(Robust p-value = 0.022)<br>BW = 0.417 |
| N | 21,204 |
| **Panel B: With covariates** | |
| Linear | -0.032<br>(Robust p-value = 0.008)<br>BW = 0.237 |
| Quadratic | -0.034<br>(Robust p-value = 0.022)<br>BW = 0.409 |
| N | 21,204 |

Covariates: age, month of deaths.
All standard errors clustered at the month of birth level.
P-values are robust-bias corrected, following Calonico et al. (2014) .

# Results


Regression Function Fit
Men
RD estimate: -0.025**
(0.011)
0
.02
.04
.06
.08
1.7
1.8
1.9
2
2.1
2.2
2.3
Sample average within bin
Polynomial fit of order 1
Regression Function Fit
Men
RD estimate: -0.029**
(0.014)
0
.02
.04
.06
.08
1.6
1.8
2
2.2
2.4
Sample average within bin
Polynomial fit of order 2

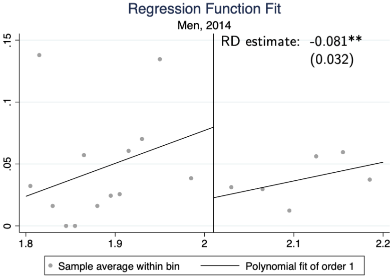
# Bandwidth Sensitivity Analysis

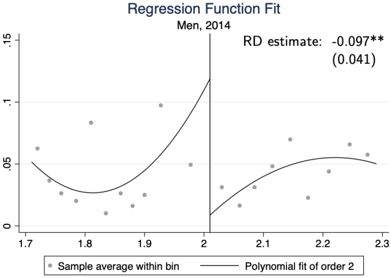



- Results persist through numerous bandwidth selections.

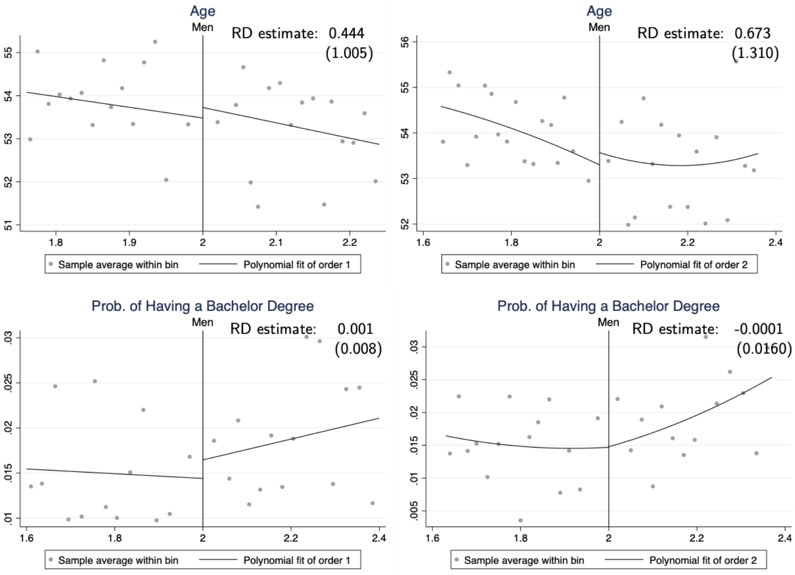
# Robustness to Manipulation - 2014 data

- As we saw earlier, if we restrict the sample to 2014, we don't have evidence of manipulation, and heaping across the running variable seems to be less of a problem;
- Our results persist in this sample, suggesting manipulation does not play an important role in driving the results.

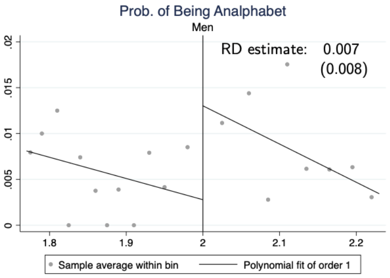


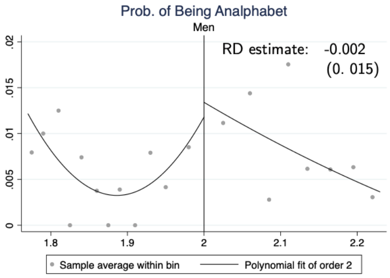



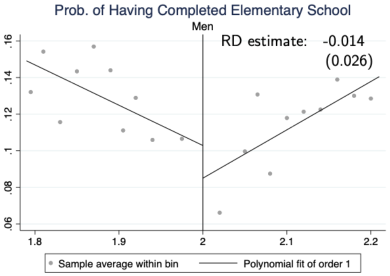
# Discontinuity on Covariates (1)

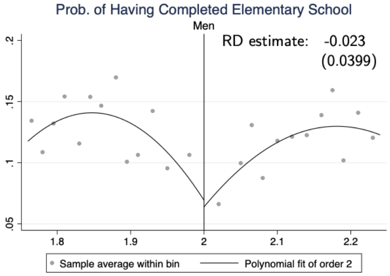


# Discontinuity on Covariates (2)

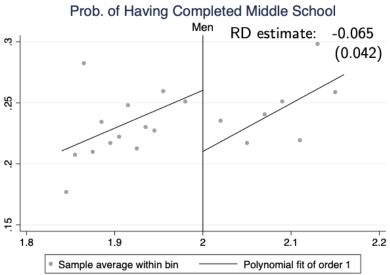


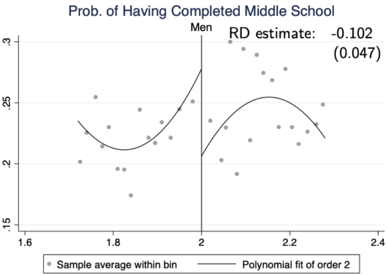



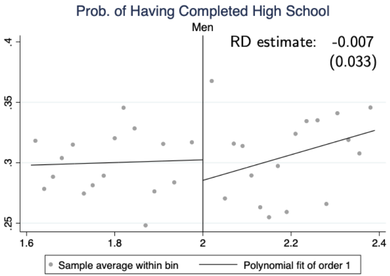



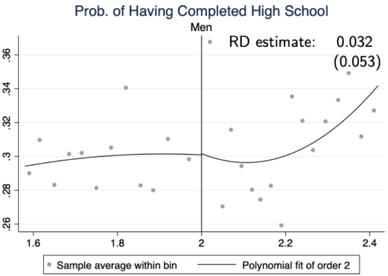



# Discontinuity on Covariates (3)



# Conclusion

- Positive liquidity shocks of a transitory nature induces behavior that favors mortality;
- Receiving a one-time payment of 50 to 100% of an individual's monthly income increases mortality in the week of payment. Such effect is temporary and there is a return to the mean in the following weeks;
- Mortality in the weeks of payment of the Abono Salarial is approx. 11% higher than other weeks for the eligible group, which translates in $\approx 1.5$ extra deaths;
- Effect is driven by male workers (power problem) and deaths by circulatory disorders and external causes;
- We believe this effect to be driven by liquidity constraints being relieved and provoking a non-smooth consumption pattern (Stephens (2003)), which in turn induces mortality (Evans & Moore (2012)).

Thank you!

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# Wild-bootrapped Standard Errors in RD

| | (1) Linear | (2) Quadratic |
|---|---|---|
| Discontinuity | -0.0301** | -0.0426** |
| | (0.0111) | (0.0145) |
| | [0.0200] | [0.0180] |
| Observations | 5615 | 9535 |

Standard-errors clustered at the month of birth level in parentheses.

Wild-bootstrap p-values in brackets.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$