On the Nature of Entrepreneurship

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Disclaimer

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This paper

- Assembles novel longitudinal database of business owners
- Estimates life-cycle income profiles for 35,000 groups
- Compares profiles for similar self- and paid-employed
  - Growth and volatility patterns
  - Analysis of entrepreneurial choice

Motivation

- Results inform:
  - Entrepreneurial theories
  - Tax administration
- Provides updated answers to:
  - Does entrepreneurship pay?
  - Is there scope for shrinking the tax gap?

Most Previous Work

- Uses surveys with
  - Top-coding
  - Short panels
- Concludes that SE (relative to peers)
  - Flatter life-cycle profiles
  - Enter SE with lower past labor income
  - Enter with higher past asset income
- Motivates theories where entrepreneurs
  - Earn large non-pecuniary benefits
  - Are misfits
  - Face liquidity constraints

In Contrast to Literature

- Use administrative data with
  - No Top-coding
  - Long panels
- Conclude that SE (relative to peers)
  - Have significantly steeper life-cycle profiles
  - Enter SE with higher past labor income
  - Enter with lower past asset income
- Motivate theories where entrepreneurs
  - Make significant investments in business
  - Experiment to learn entrepreneurial productivity
  - Face few liquidity constraints

Today's talk

- Data
  - Sample
  - Income measures
  - Skill and education imputations
- Life-cycle profile estimation
  - Potential challenges
  - Econometric approach
  - Income and growth profiles by group
- Entrepreneurial choice
  - Entry and exit
  - Characteristics of entrants
- Theoretical predictions

Data

Sample

- Primary source: administrative IRS data
  - Balanced panel of living individuals with US SSN
  - Birth cohorts 1950-1975
  - Available 1996-2015
- Merge in: Schedule C and K-1 data
  - Owners of pass-through businesses
  - Available 2000-present

Income Measures

- Self-employment (SE) income
  - Schedule C net profit of sole proprietors
  - Schedule K-1 ordinary business income of
    - Individual partners
    - S-corporation owners
  - W-2 wages of S-corporation owners
- Paid-employment (PE) income
  - W-2 wages of non-owner employees

Employment Status

- Self-employed (SE) in a given year if:
  - |SE income| $>$ 5,000 in 2012\$ **and**

    $$\left.\begin{array}{l} |\text{SE income}| > |\text{PE income}| \\ \text{Share in business} \times \text{employees} \geq 1 \\ \text{Share of gross profits} > \text{PE income} \end{array}\right\} \text{At least one}$$

- Paid-employed (PE) in a given year if:
  - Not SE
  - W-2 earnings $>$ 5,000 in 2012\$
- Non-employed (NE) in a given year if:
  - Not SE or PE

Skill and Education Measures

Skills:

- Individuals with occupation in e-filing
  - Map entry to SOC code
  - Map SOC to cognitive, interpersonal, and manual skills
- Individuals with missing codes
  - Develop classifier code based on CPS
  - Use regression results with IRS data

Education:

- Individuals classified as educated if
  - Occupation listed as student
  - Filed 1098-T
  - CPS-based classifier indicates so

Sample Statistics

Statistic	Total Sample	Attached PE	Attached SE	Mostly Switching	Any NE
Individuals (Mil)	65.0	35.4	1.9	2.2	24.8
Incomes (2012 $, Th.)					
Mean income	53.5	65.6	154.4	103.3	22.2
Income, 10^{th} pctl	6.7	23.7	17.3	17.9	2.1
50^{th}	35.9	49.7	66.8	53.2	14.3
90^{th}	99.7	110.9	334.8	206.2	44.8
Skills (%)					
Educated	52.1	59.6	61.6	63.7	39.3
Cognitive	47.2	52.7	59.9	58.6	37.0
Interpersonal	56.1	63.1	58.7	62.8	45.0
Manual	32.3	31.1	32.7	30.1	34.2
Demographics					
Male (%)	50.7	53.4	82.4	75.1	41.5
Mostly married (%)	67.6	70.3	79.1	75.4	61.9

Life-cycle Profile Estimation

Comparisons of Self- and Paid-Employed

- Central to the analysis is SE vs PE comparisons
- Idea:
  - Only self-employed rewarded for firm-specific investment
  - Can compare self- and paid-employed with
    - Same demographics, industry, education, etc.
    - Different investment opportunities
  - Look for differences in life-cycle income growth profiles

Object of Interest

$$\text{Income}(\text{Age} \mid \text{Individual and aggregate factors})$$

Challenges

- Selection
  - Incomes driven by latent characteristics
  - $\Rightarrow$ Allow for unrestricted intercept
- Survival
  - Income higher because successful remain
  - $\Rightarrow$ Study "attached" and "switchers" separately
- Identification
  - Time and age effects not separately identified
  - $\Rightarrow$ Exploit overlapping cohorts
- Signs
  - Business incomes can be negative
  - $\Rightarrow$ Estimate in levels with flexible error structure

Estimation Procedure

- Estimate time (β) and age (γ) effects for income:

$$y_{it} = \alpha_i + \beta_{g(i),t} + \sum_{a=a_0}^{a(i,t)} \gamma^a_{c(i),g(i)} + \epsilon_{i,t}$$

  where

  - $i \in \mathcal{I}$ is set of individuals
  - $t \in \mathcal{T}$ is set of calendar dates
  - $c \in \mathcal{C}$ is set of birth years
  - $a \in \mathcal{A}$ is set of ages
  - $g \in \mathcal{G}$ is set of groups partitioning $\mathcal{I}$

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- Requires assumptions to separately identify β and γ

Identification

- Two identifying assumptions
  - Age effects are same across cohorts, $\gamma^a_{c,g} = \overline{\gamma}^a_g$
  - Average time effect satisfies (where $\overline{y}_{g,t_0}$ is avg income for g):

$$\frac{\overline{\Delta\beta_g}}{\overline{y}_{g,t_0}} = \frac{\mu_g}{T}\sum_t (1+\mu_g)^t$$

- Allows flexibility when set $\mathcal{G}$ large

A Practical Footnote: Easy to do

- Using least-squares approach

$$\min_{\{\Delta\beta_g, \overline{\gamma}_g^a\}} \sum_{g\in\mathcal{G}} \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \left(\Delta y_{it} - \Delta\beta_{g(i),t} - \overline{\gamma}_{g(i)}^{a(i,t)} \right)^2$$

$\Rightarrow$ Solving small linear systems for each g

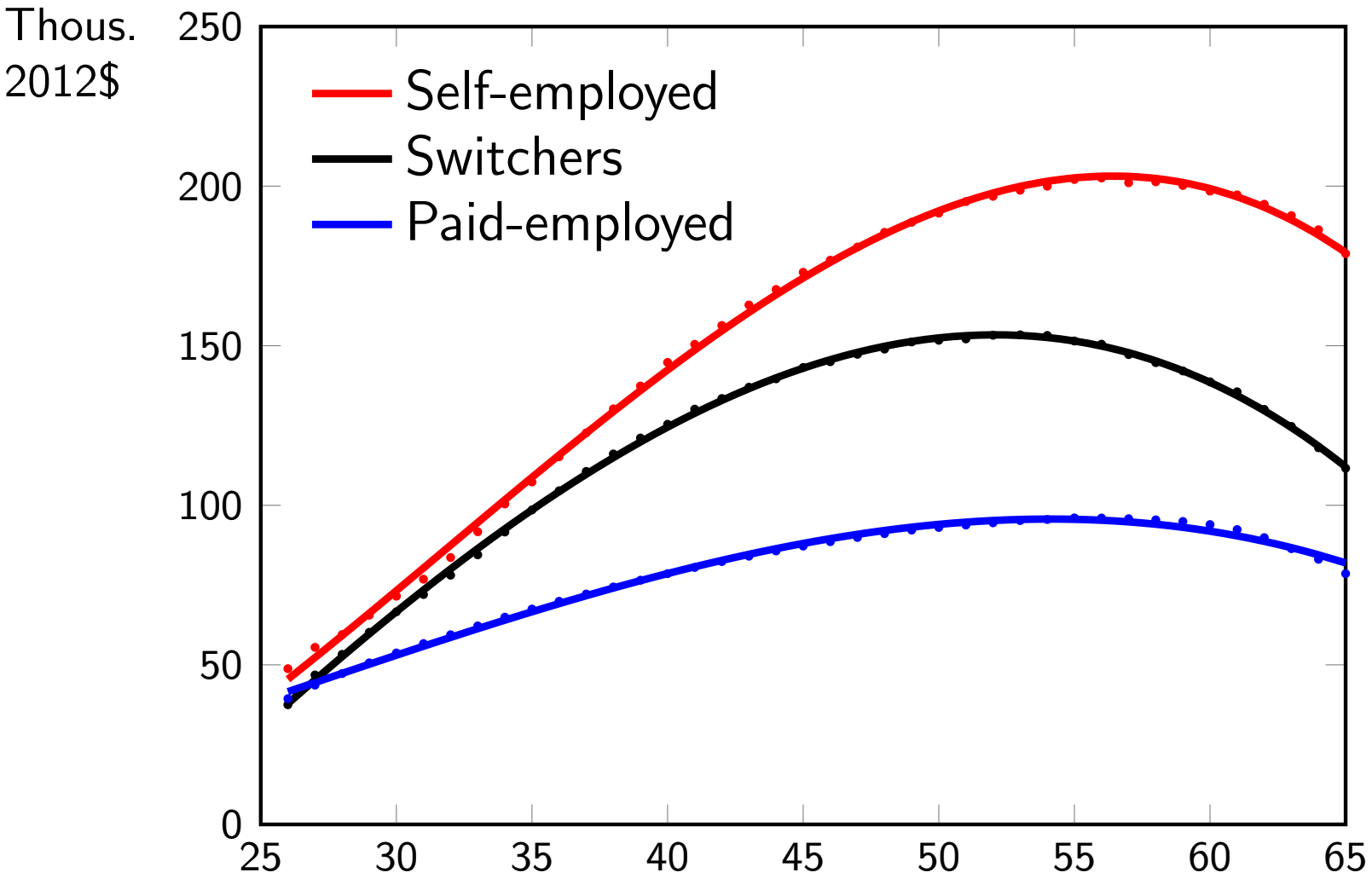
$$\begin{pmatrix} \text{Population} \\ \text{Counts} \\ \text{for} \\ \text{different} \\ \text{ages and} \\ \text{times} \end{pmatrix} \begin{pmatrix} \Delta\beta_g^{2001} \\ \vdots \\ \Delta\beta_g^{2015} \\ \overline{\gamma}_g^{26} \\ \vdots \\ \overline{\gamma}_g^{65} \end{pmatrix} = \begin{pmatrix} \text{Avg.} \\ \text{Incomes} \\ \text{at} \\ \text{different} \\ \text{ages and} \\ \text{times} \end{pmatrix}$$

Application: set $\mathcal{G}$ with 35,117 groups

- Employment attachment:
  - Attached to SE (1.9 mil) or to PE (35.4 mil)
  - Almost attached to SE (0.3 mil) or to PE (0.5 mil)
  - Mostly switching (2.2 mil)
  - Any NE (24.8 mil)
- Other observables:
  - Cohort (50-59, 60-69, 70-75)
  - Gender (M/F)
  - Educated (yes/no)
  - Skilled cognitively, interpersonally, mannually (yes/no's)
  - Industry (20 2-digit)
  - Married (9 or more years, yes/no)
  - Children (have/don't have)

Empirical Results: Time and Age Effects

Income Profiles



- Does entrepreneurship pay? Yes

Estimated Time Effects Relative to Total

- Flexible approach allows for differences in 2008-09

Estimated Age Effects for Attached SE and PE

- Significantly higher and more persistent growth for SE

Disaggregating Trends

Rich data allows for disaggregated analysis

- For example:
  - Men

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- For example:
  - Men
  - Married

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  - Interpersonally skilled

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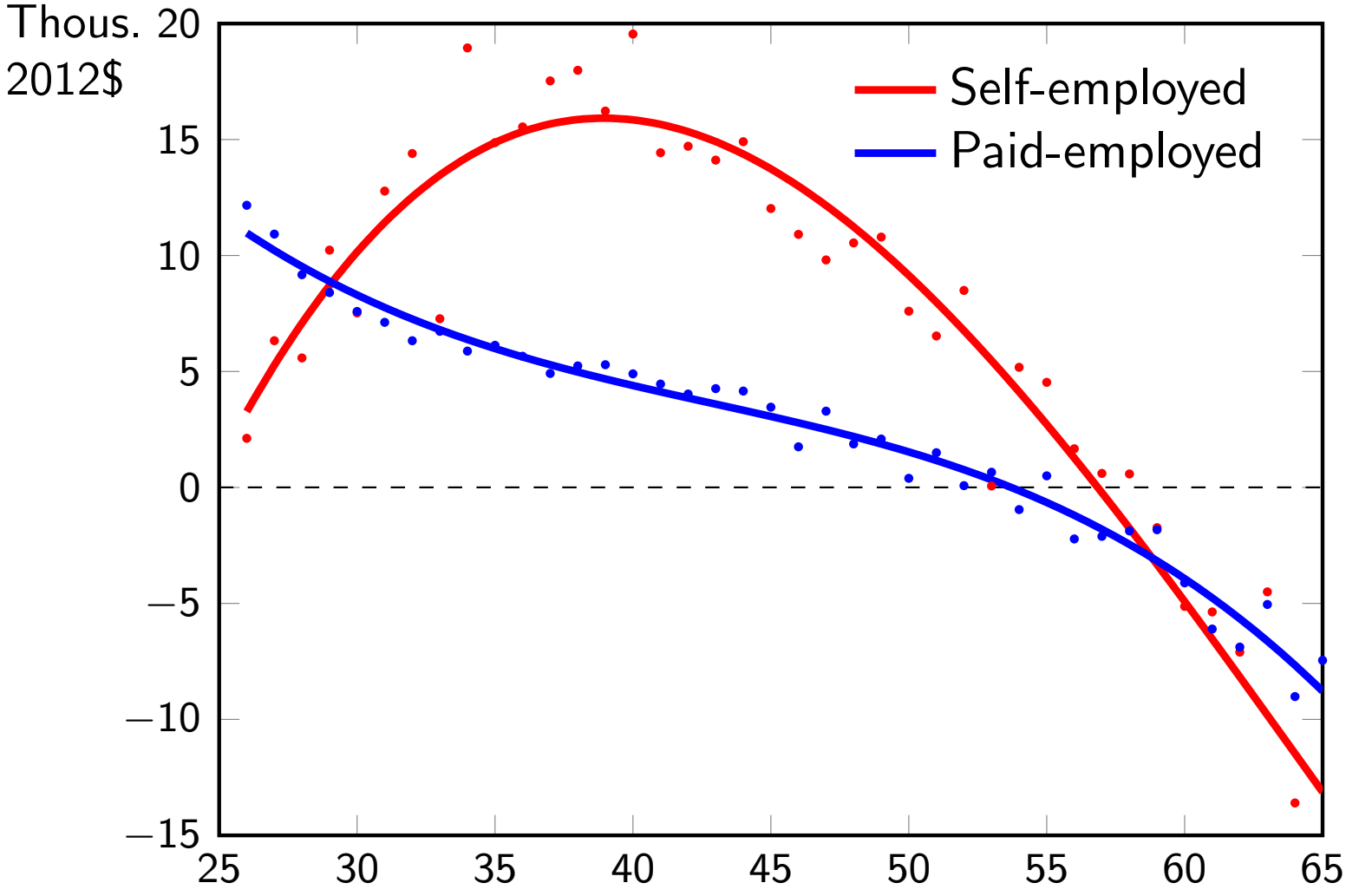
Just two of our 35,117 groups

Estimated Age Effects For the Detailed Group



- Even more pronounced hump

Growth Gap Decomposition

Cumulative Share	Characteristics						
	Industry	Male	Married	Educated	Interpersonal	Cognitive	Manual
15.4							
26.7							
33.1							
39.4							
44.9							
49.3							
53.5							

- Small number of groups account for most of growth gap

Growth Gap Decomposition

Cumulative Share	Characteristics						
	Industry	Male	Married	Educated	Interpersonal	Cognitive	Manual
15.4	Health						
26.7	Prof.						
33.1	Prof.						
39.4	Finance						
44.9	Health						
49.3	Retail						
53.5	Constr.						

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39.4	Finance	√	√	√	√		
44.9	Health	√	√	√	√		
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39.4	Finance	√	√	√	√		
44.9	Health	√	√	√	√	√	√
49.3	Retail	√	√	√	√	√	
53.5	Constr.	√	√	√	√	√	

- Small number of groups account for most of growth gap

Empirical Results: Tracking the Dollars

Tracking the Dollars

- For each industry, cohort, gender
  - Rank individuals by average income
  - Construct income shares by percentile
- Aggregate using population counts

Typical Dollar

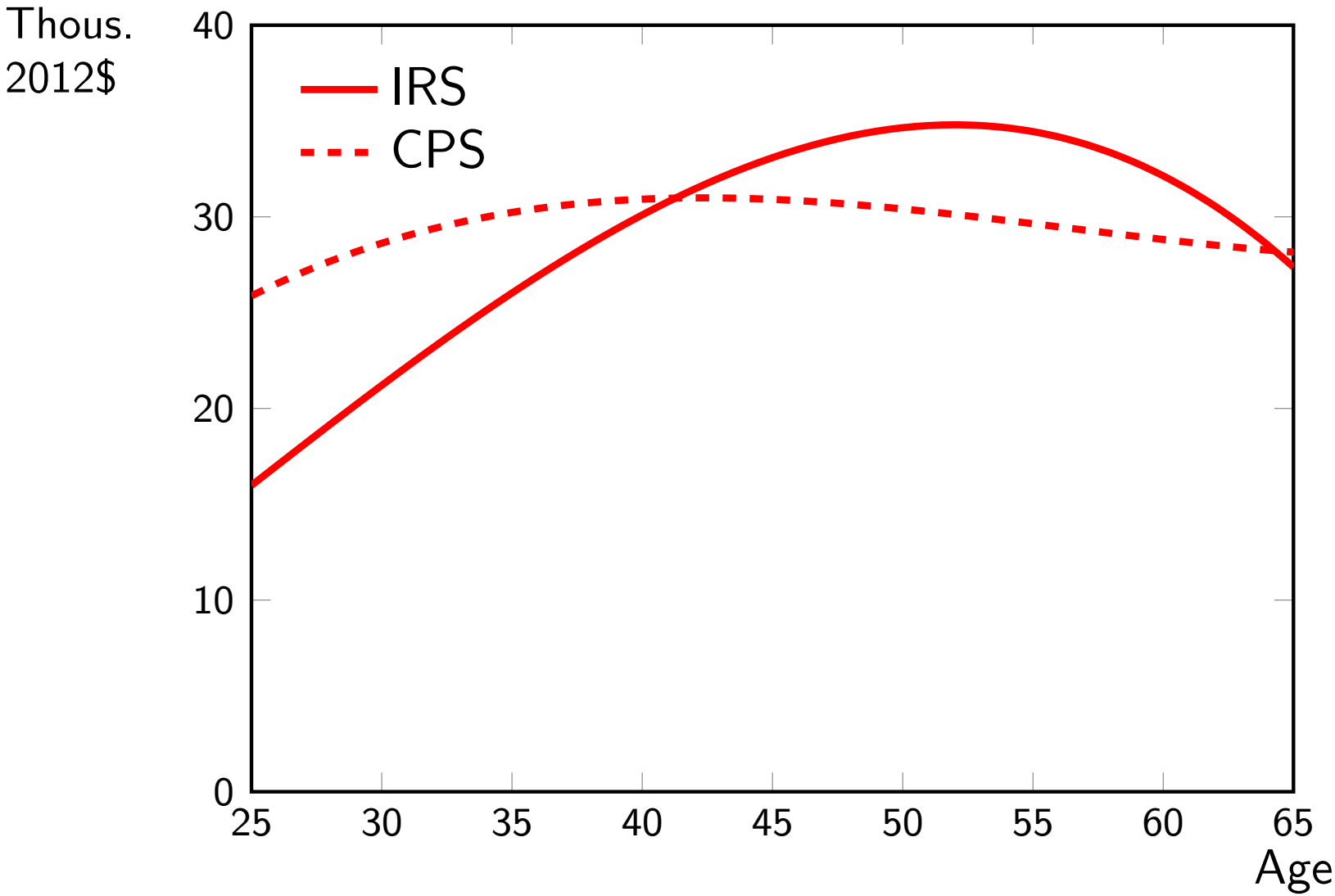
Percentile Group	Income Share All	Self	Paid
$< 10^{th}$	0.8	-1.5	1.1
10^{th} to 25^{th}	4.4	3.0	4.7
25^{th} to 75^{th}	36.8	18.6	39.9
75^{th} to 90^{th}	21.8	15.8	22.8
$> 90^{th}$	36.2	64.1	31.5

- 80% of entrepreneurial income
  - In 75+ percentile of income shares
  - Not observable in top-coded survey samples

What is Observed in Surveys?

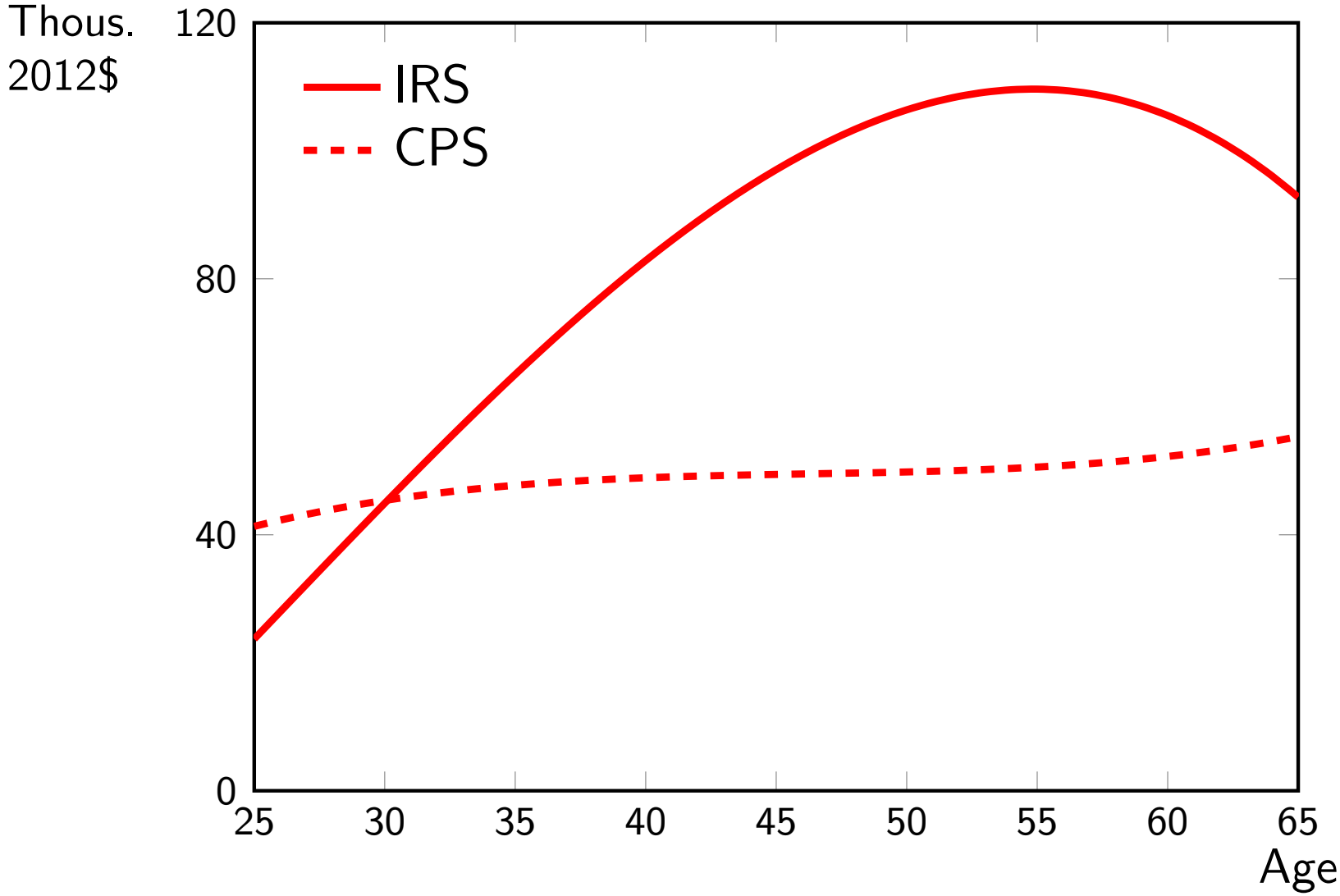
- Use same criteria for assigning SE vs PE
- Compare empirical moments for IRS vs CPS
  - Medians for population
  - Means for population
  - Means for "big-gap" guys

SE Median Income



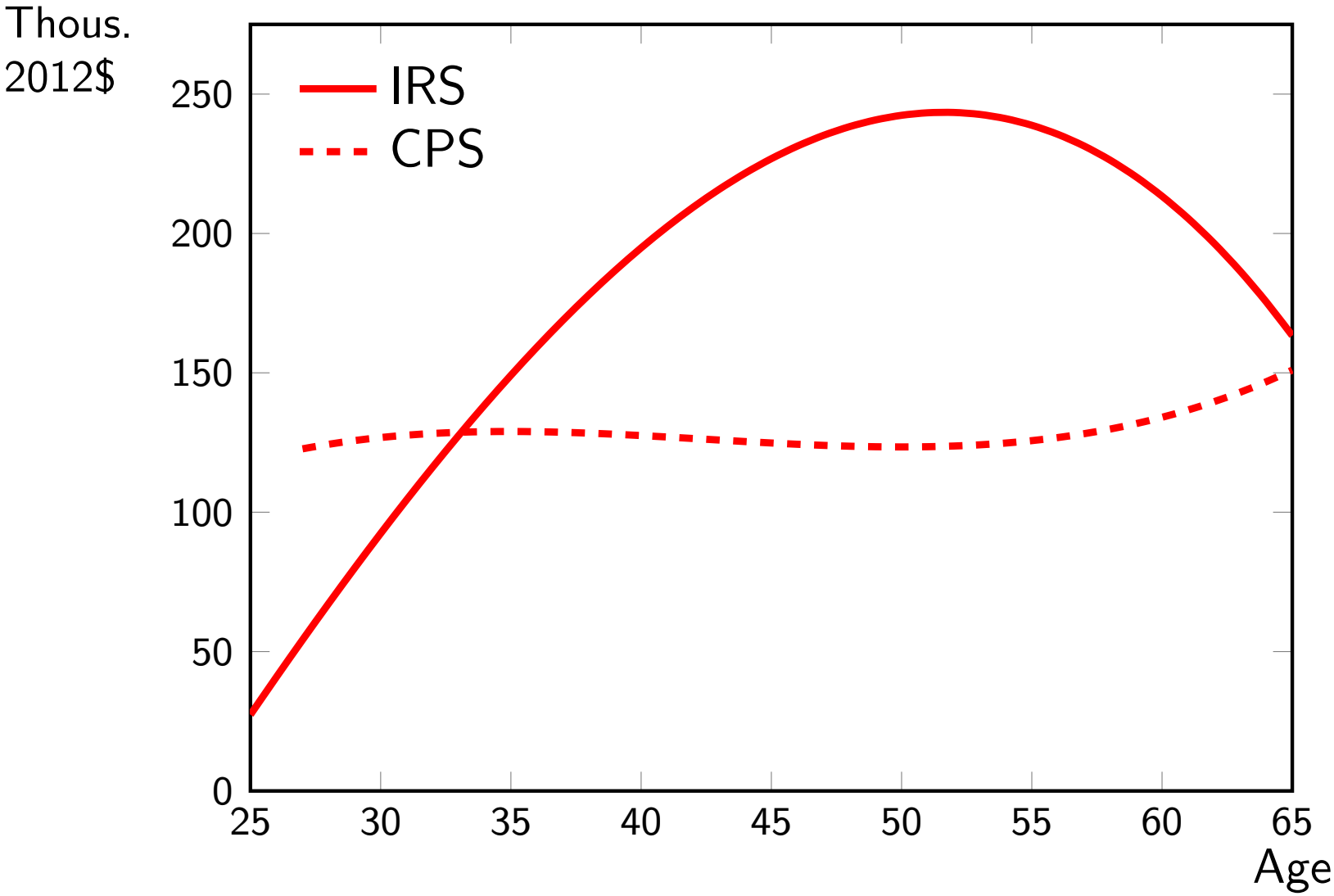
- Broadly similar

SE Mean Income



- Starkly different

"Big-Gap Guys" SE Mean



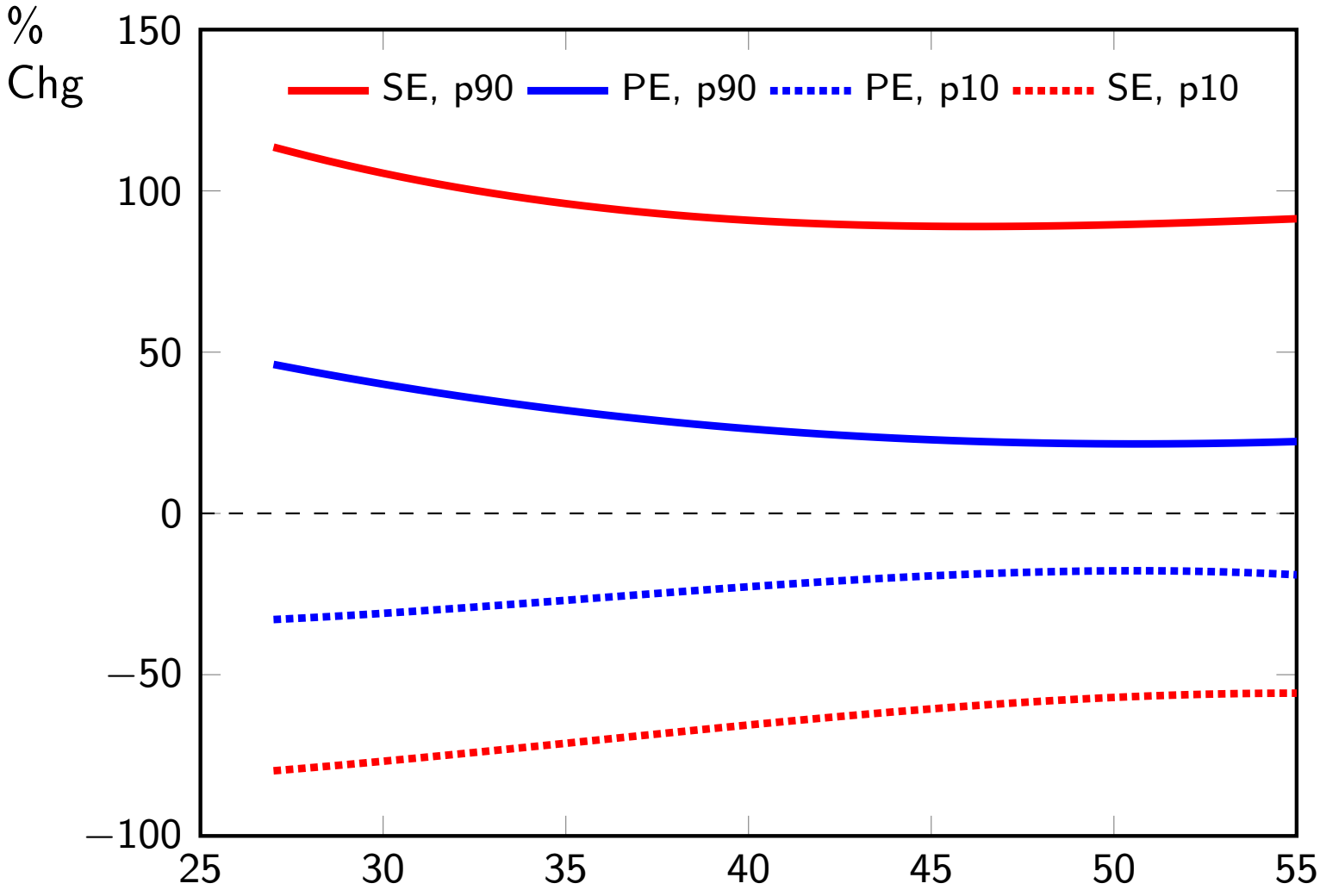
- And still no growth in CPS

Empirical Results: Volatility Patterns

Volatility Patterns

- Two measures:
  - Transition matrices on residuals $\Delta\epsilon_{i,t}$
  - Percentiles of income changes $\Delta\epsilon_{i,a}/|y_{i,a-1}|$
- Both show more volatility in SE but
  - Decreasing across age
  - Inconsistent with theories of risk
- Next, consider income changes at 10^{th} and 90^{th} percentile

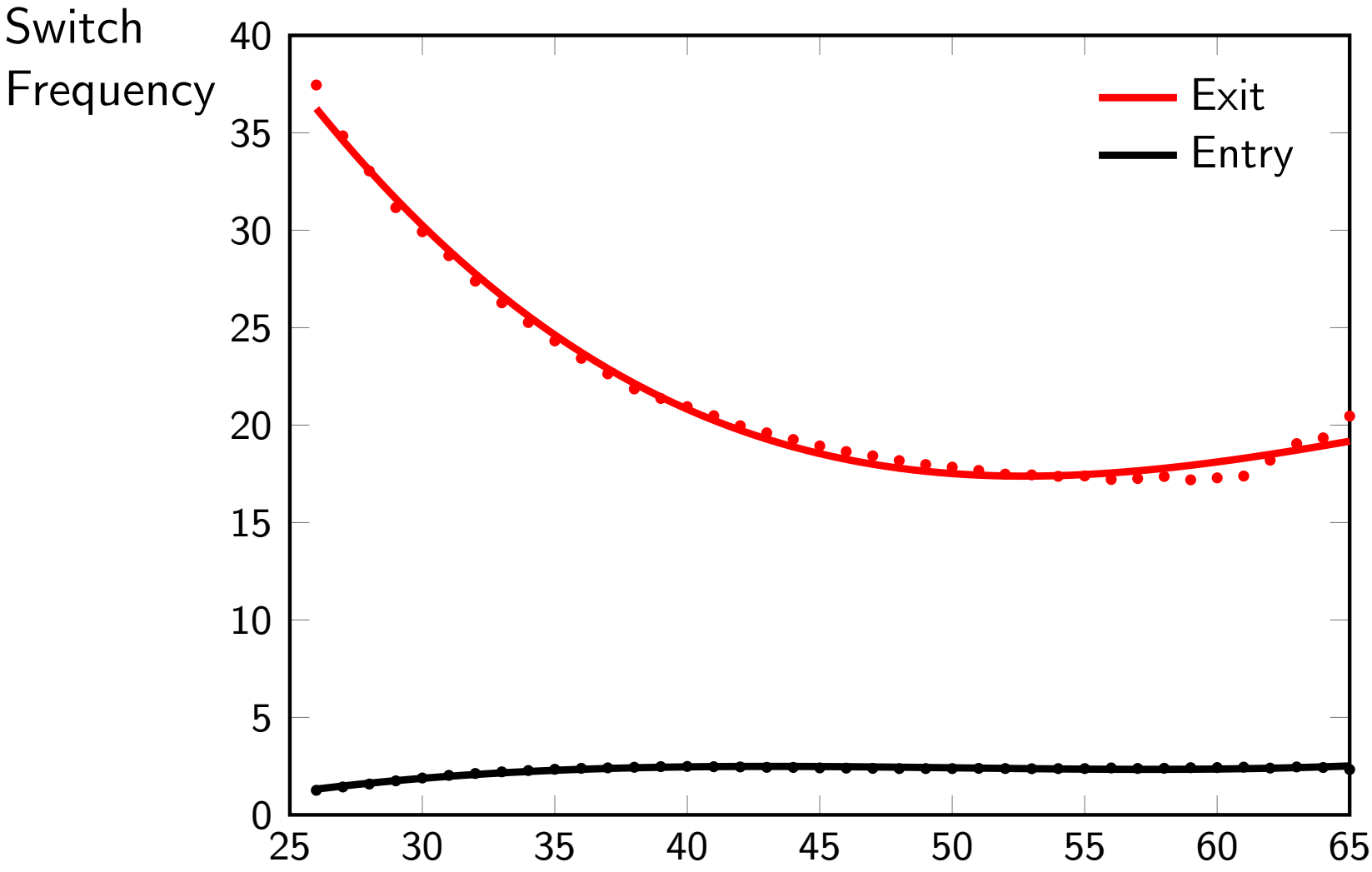
Income Changes for Attached SE and PE



- Around 2 to 3 times more volatility in SE

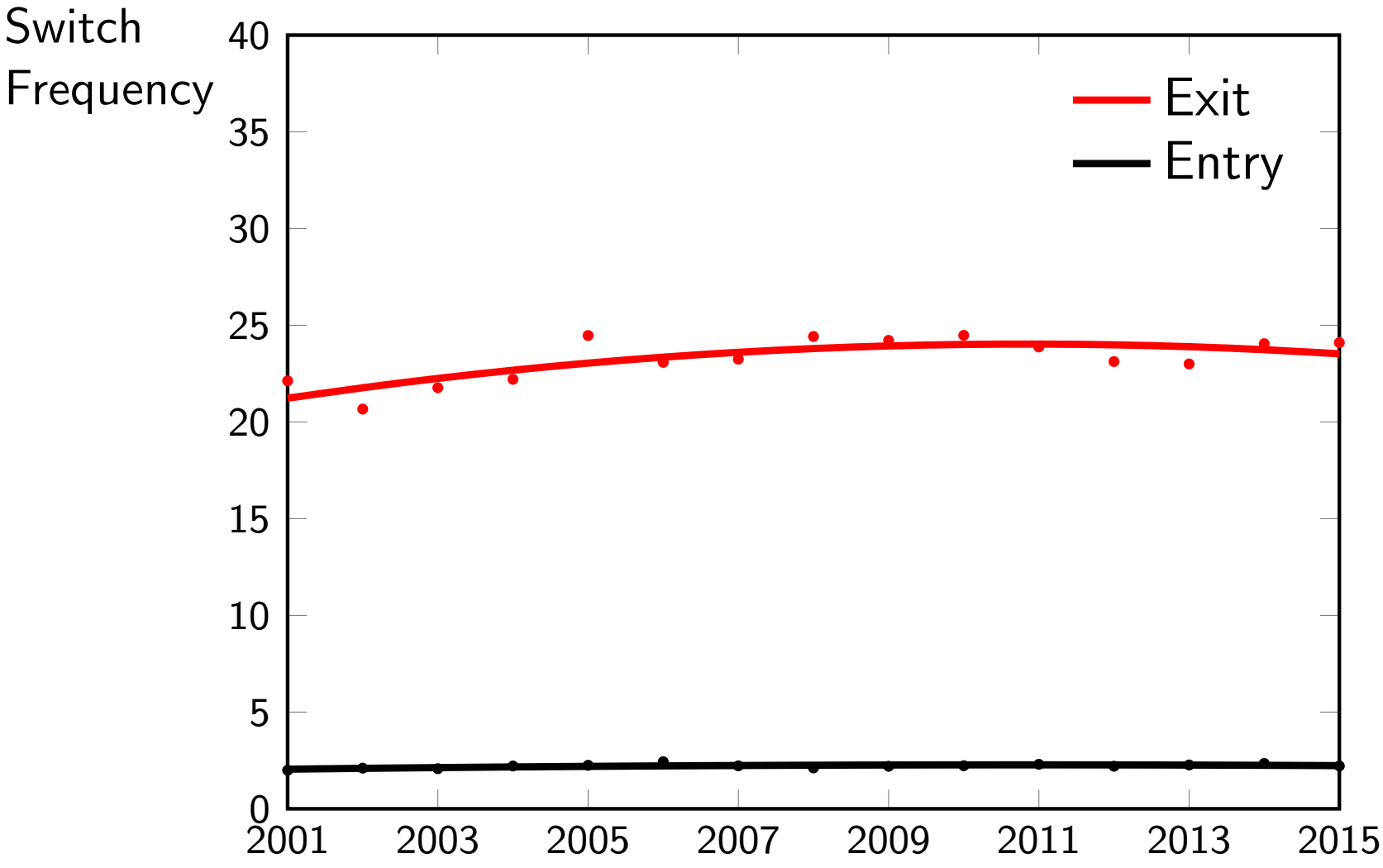
Entrepreneurial Choice: Entry and Exit

Entry to and Exit from SE by Age



- Suggests early experimentation and learning

Entry to and Exit from SE by Year



- Suggests SE not a hedge against unemployment risk

Entrepreneurial Choice: Determinants of Self-Employment

Determinants of Self-Employment

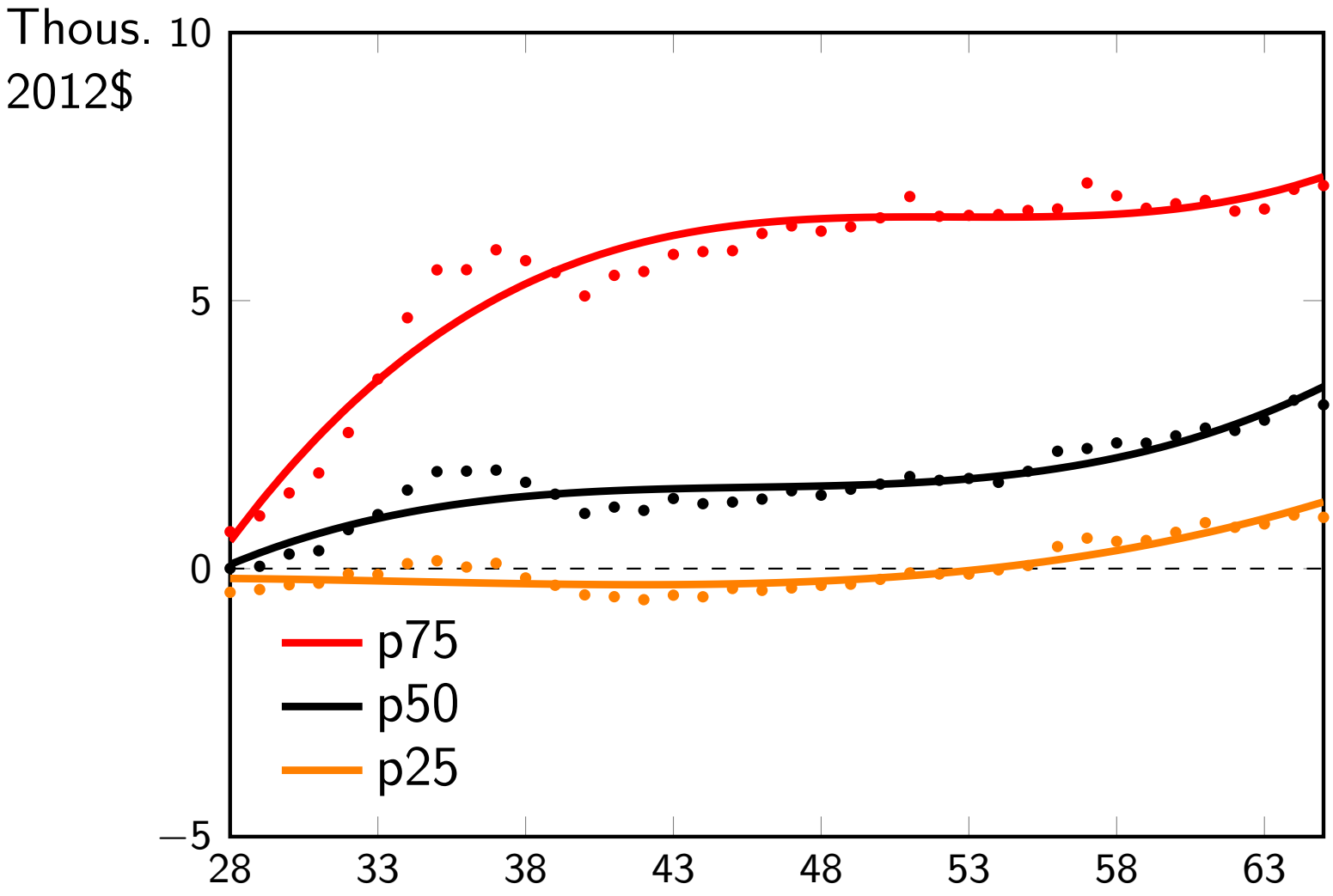
- Compare outcomes of SE entrants to "similar" non-switchers
  - One-time entrants into SE ("Treatment")
  - Non-switchers with same characteristics ("Control")
- Assess "misfit" hypothesis for SE
  - Have low past income
  - Use SE as fallback option

Determinants of Self-Employment

- Idea:
  - Compute average PE income before switch (3 years)
  - Compare income of i with matched peers $m(i)$
  - Use cohort, gender, NAICS for matches
- Compare differences:

$$\Delta_{it} = \frac{1}{3}\sum_{j} y_{i,t-j} - \frac{1}{3N_{m(i)}}\sum_{m(i)}\sum_{j} y_{m(i),t-j} \tag{1}$$

Past Wage Income: Switchers vs Non-switchers

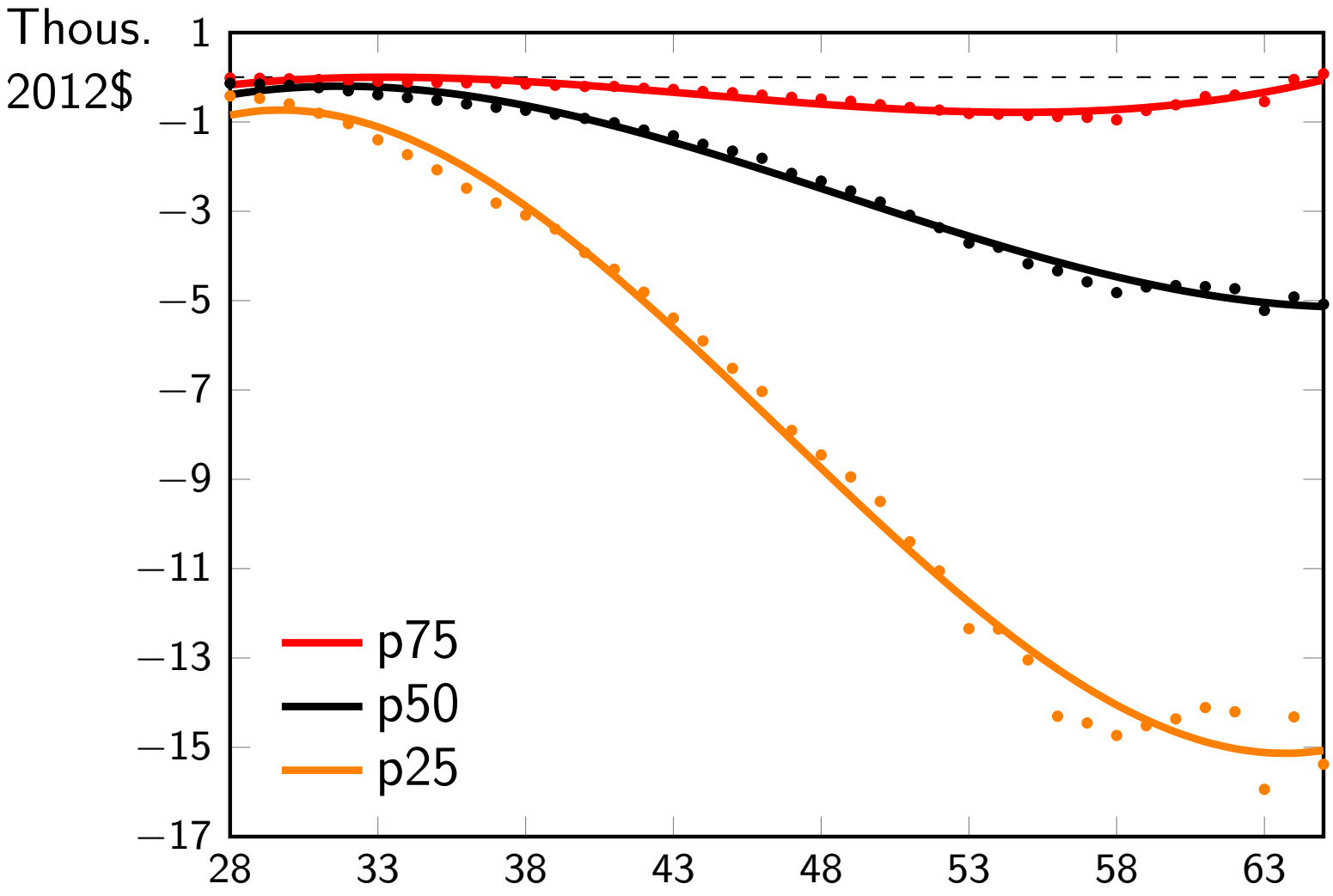


- Suggests that SE have higher past wage income before entry

Repeat Exercise with Asset Income

- Assess "financial-friction" hypothesis
  - Have high past income
  - Need financing to start businesses
- Condition also on percentile of past income

Past Asset Income: Switchers vs Non-switchers



- Suggests that SE have lower asset income before entry

Informing Theory

Empirically-Motivated Features

- Two features suggested by empirical results:
  - Investment in self-created intangible assets
  - Incomplete information about entrepreneurial productivity
- Why self-created intangibles needed?
  - Owners invest time building customer-bases, brands, etc
  - Investment implies high, persistent income growth
- Why incomplete information needed?
  - Owners require time to learn their productivity
  - Learning implies declining exit rates

$\Rightarrow$ Added to decision theoretic problem dynamic program

A Theoretical Case Study: Young Entrepreneurs

Predictions for Young Entrepreneurs

- Choose parameters consistent with IRS micro data
- Simulate model time series over the life cycle
- Aggregate simulations using IRS counts and entry ages
- Construct growth profiles for young SE stayers/switchers

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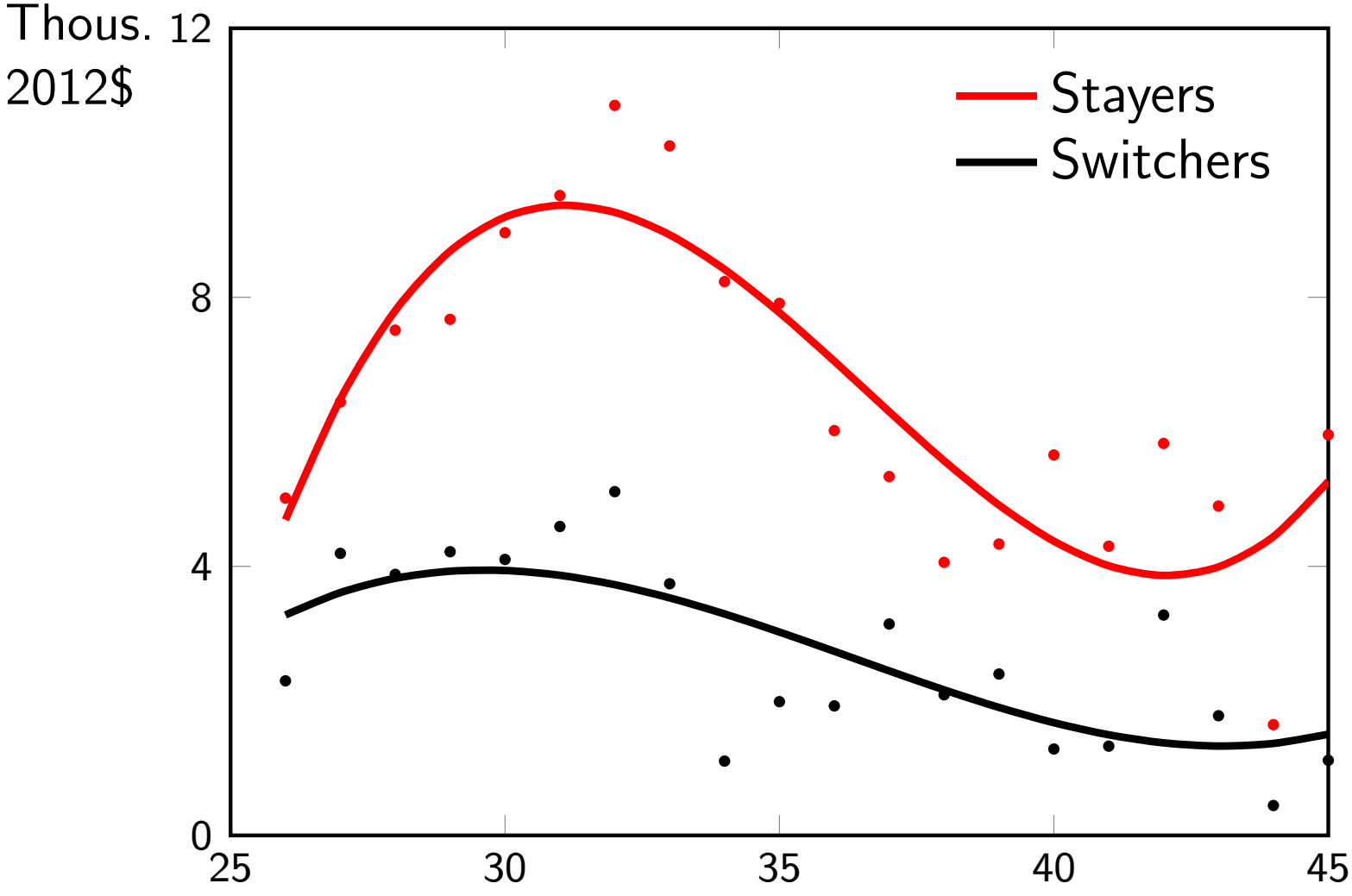
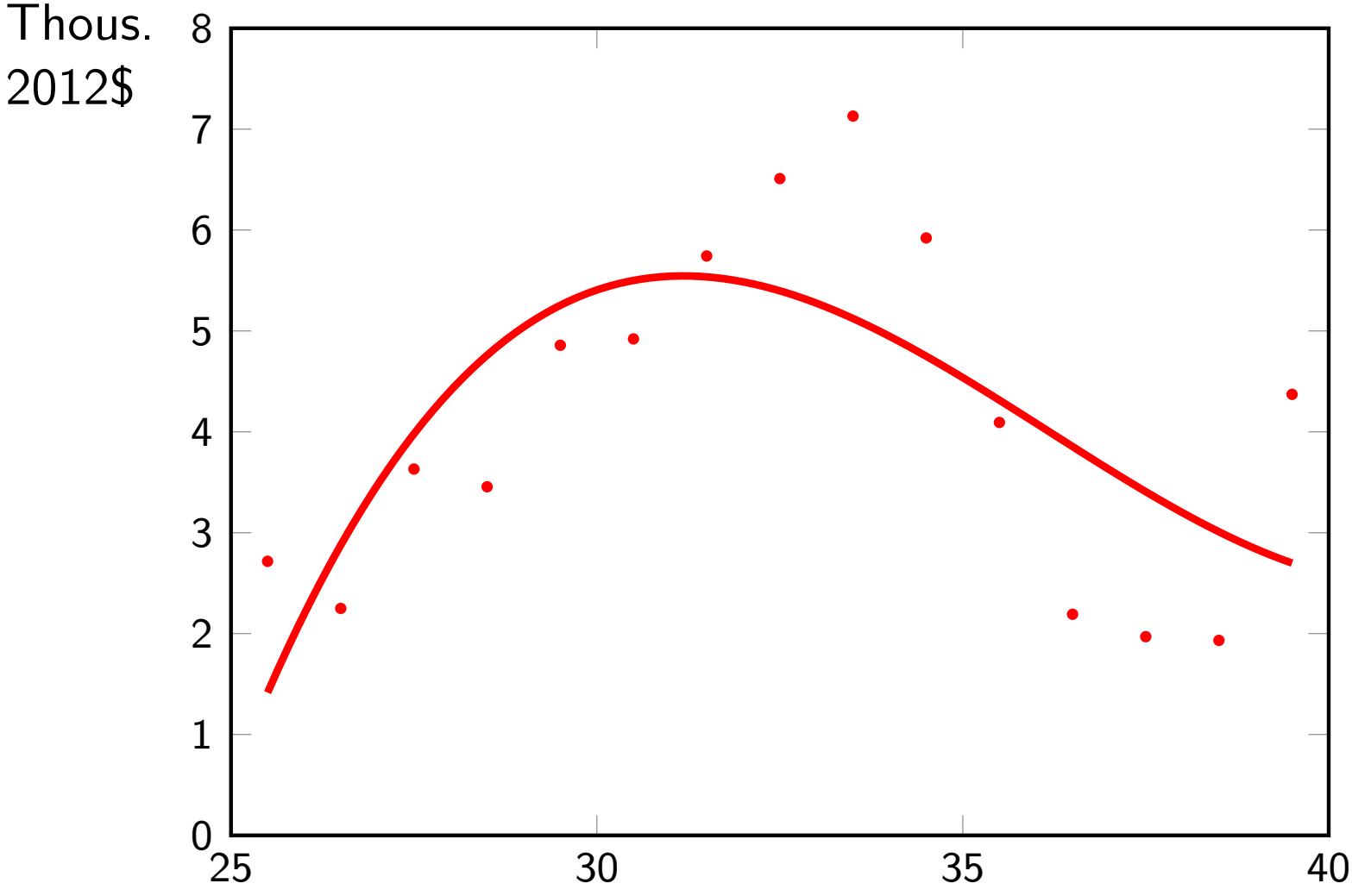
Let's start with the data...

1970-75 Cohort with 5+ Years SE Experience



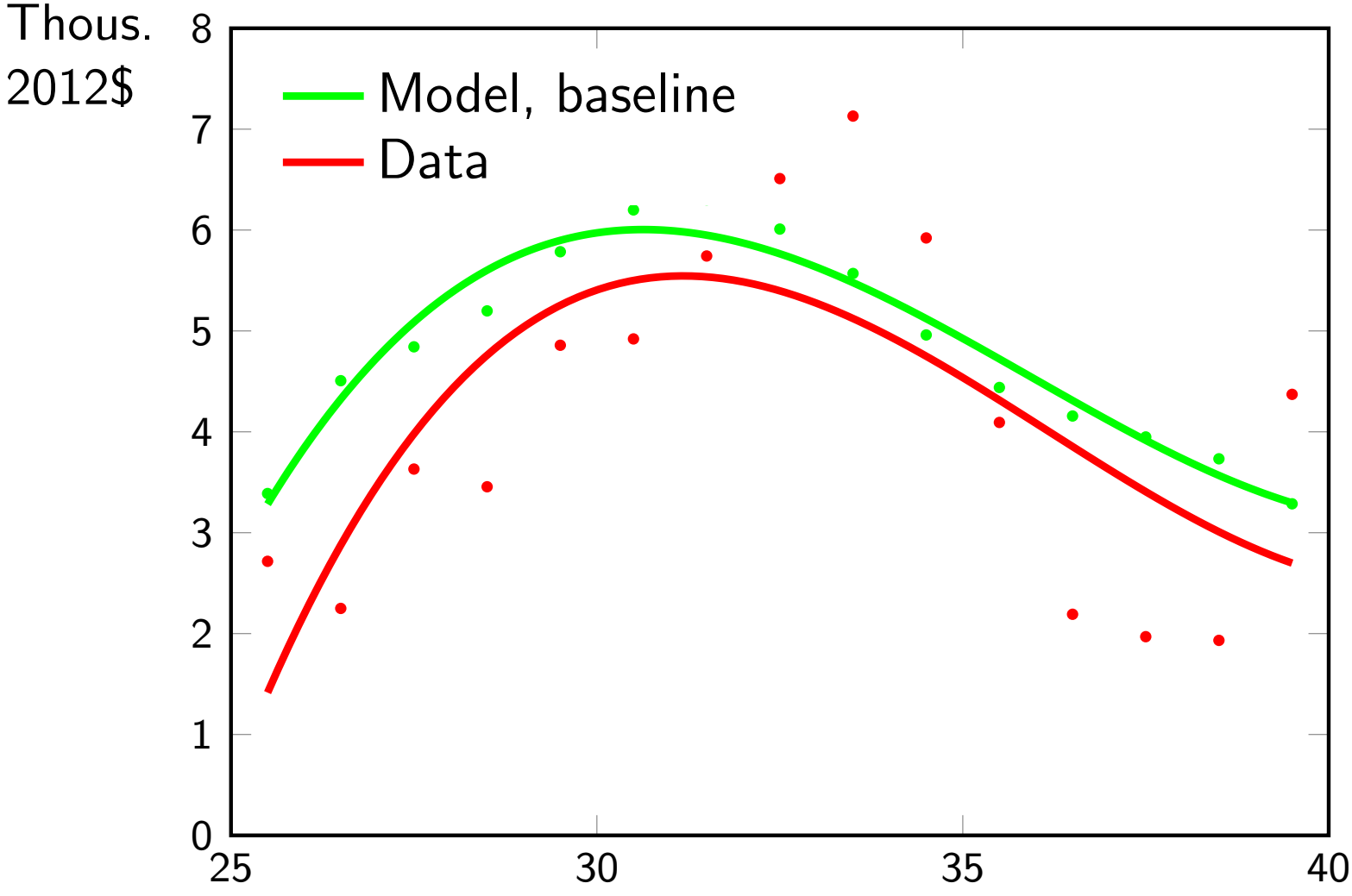
- Use results to construct growth differential for data

Growth Differential for Young Entrepreneurs



- Suggests SE stayers different than switchers even early on

Growth Differentials for Young Entrepreneurs



- Theory generates comparable growth pattern

Summary

- Assembled novel longitudinal database for business owners
- Estimated life-cycle income profiles for many groups
- Developed prototype model of entrepreneurs
- Studied model predictions for IRS data

Dynamic Program

$$
\begin{aligned}
V_k(s) &= \max_{c,h_y,h_\kappa,k,n,e} \{U(c,\ell) + \beta EV(s')\} \\
a' &= (1+r)a + pe^z f_y(\kappa, h_y, k, n) - (r+\delta_k)k - wn - e - c \geq 0 \\
\kappa' &= (1-\delta_\kappa)\kappa + f_\kappa(h_\kappa, e) \\
\ell &= 1 - h_y - h_\kappa
\end{aligned}
$$

where

$s = [a, \kappa, j, \epsilon, z, \mu]$

$j' = j + 1$ and j is age

$\epsilon' =$ a Markov chain given productivity

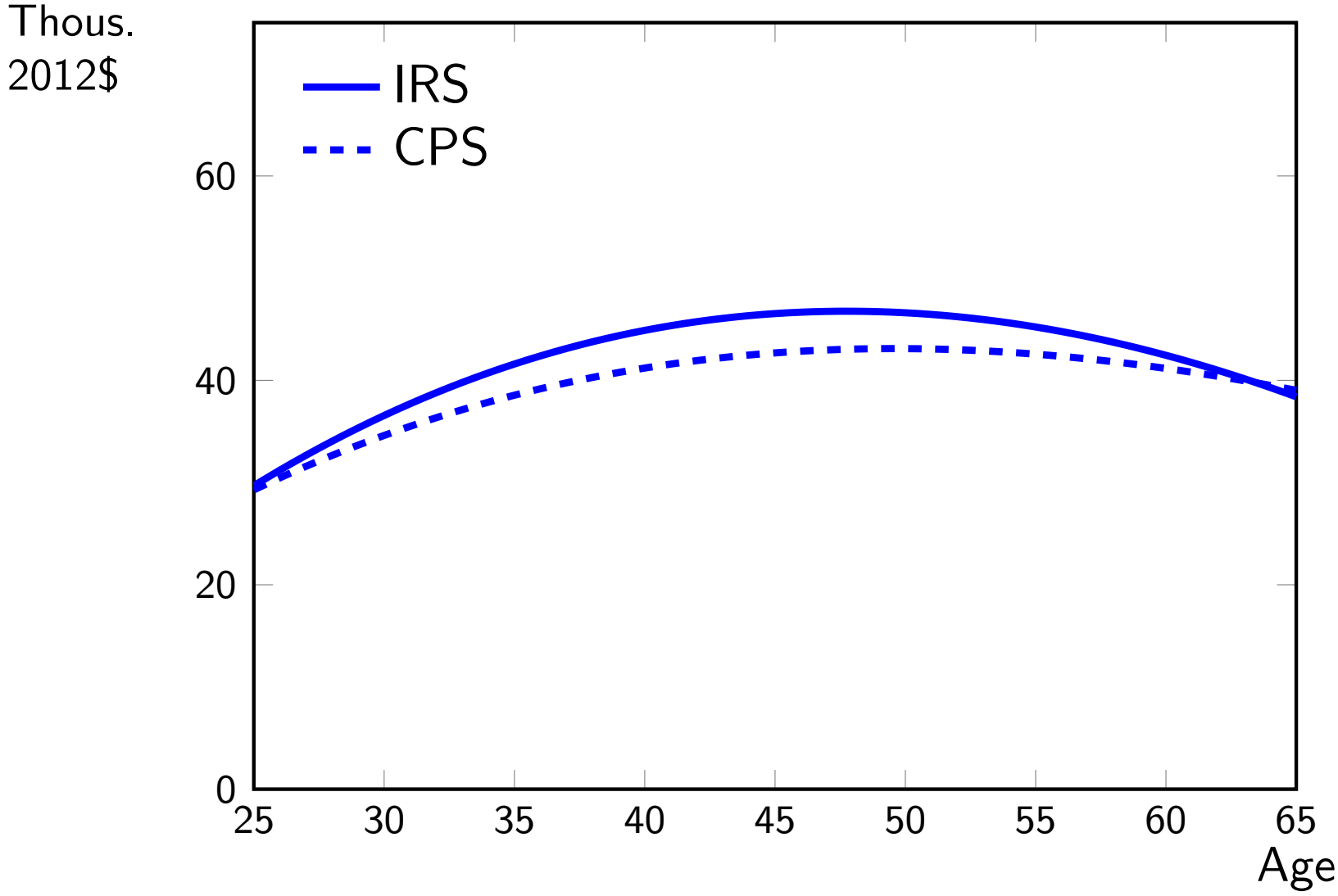
$z_j = \bar{z}_0 + \eta_j$ given $\eta_j \sim N(0, \sigma_\eta^2)$ and productivity z_j

$\mu_j = \mu_{j-1} + \sigma_{j-1}^2 (z_{j-1} - \mu_{j-1})/(\sigma_{j-1}^2 + \sigma_\eta^2)$

$\sigma_j^2 = \sigma_{j-1}^2 \sigma_\eta^2/(\sigma_{j-1}^2 + \sigma_\eta^2)$

back

PE Median Income



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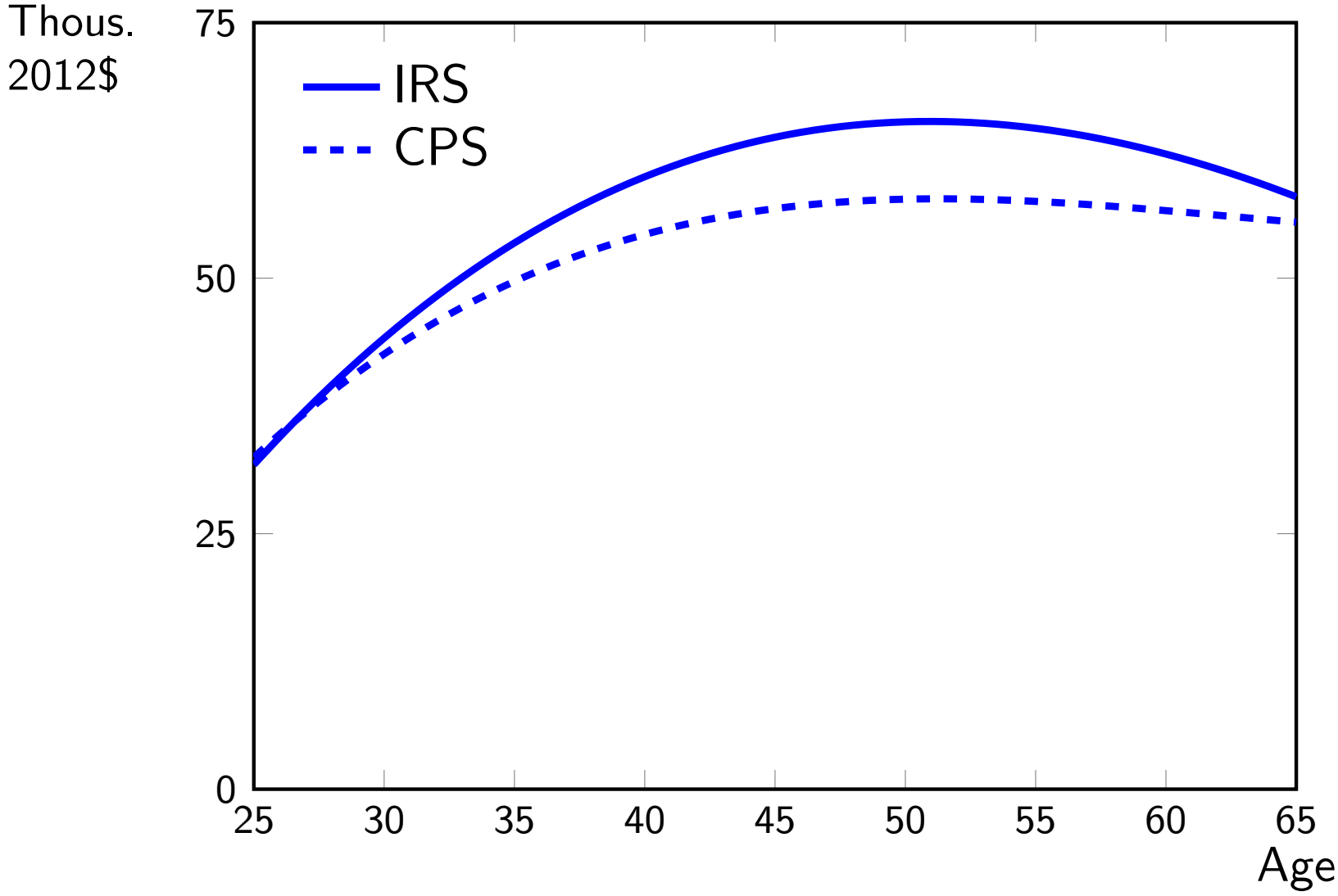
PE Mean Income



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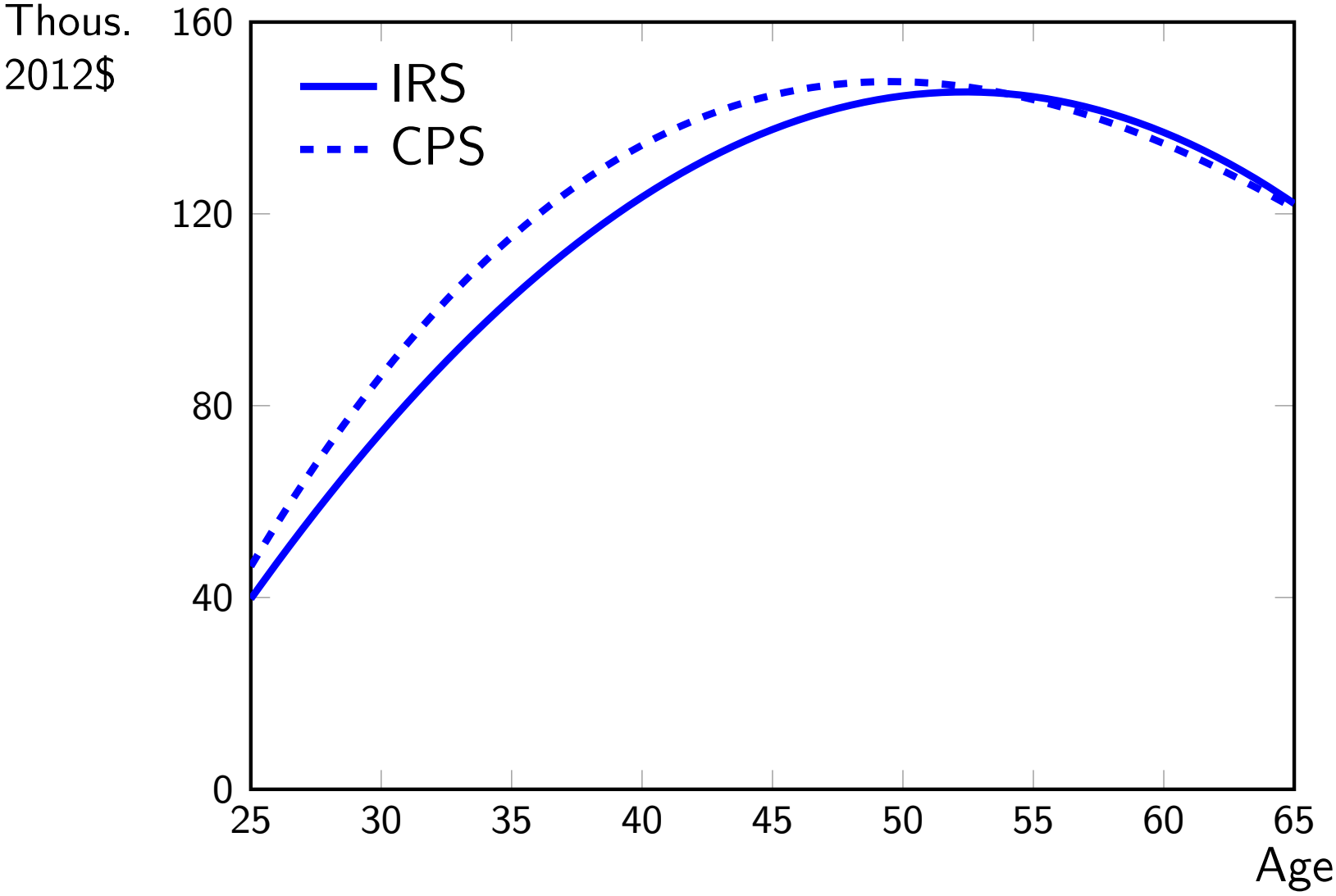
"Big Gap Guys" PE Mean



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