Does Algorithmic Trading Improve Liquidity?

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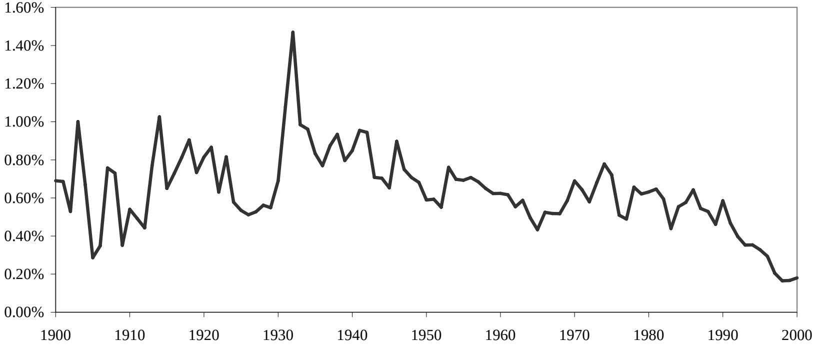
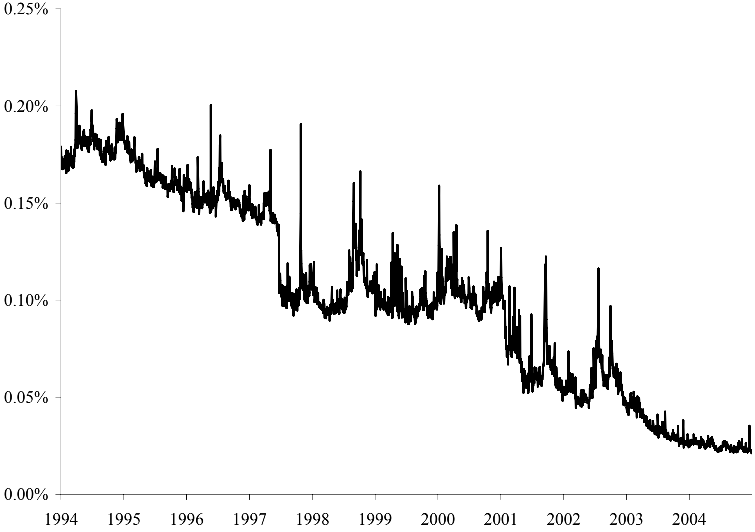
Time trend bid-ask spread (ctd)

Relative bid-ask spread Dow Jones stocks
(all stocks 1900-1928, DJIA stocks 1929-2000)



Time trend bid-ask spread (ctd)

NYSE value-weighted average effective spread



Institutional trading

How do institutions trade prior to algorithms? To buy 100,000 IBM shares, they

- hire a broker-dealer to take down or shop a block
- hire NYSE floor broker who uses judgement to slowly "work" the order

Broker-dealers now offer algos that minimize price concession through a dynamic trading strategy that optimizes over price, quantity, time, and venue

And, broker-dealers and hedge funds supply liquidity with algos (e.g. D.E. Shaw, Getco,...)

Related literature

IO of liquidity supply

- competition: Kyle (1985), Biais, Martimort, and Rochet (2000)

Free trading option of limit orders (Copeland and Galai (1983))

- monitoring public information flow is costly (Foucault, Roëll, and Sandas (2003))
- AT may raise costs of non-AT limit orders (Rock (1990))

Optimal execution of large orders (Keim and Madhavan (1995), Bertsimas and Lo (1998), Almgren and Chriss (2000))

- market vs. limit, aggressiveness (Harris (1998), Griffiths, Smith, Turnbull, and White (2000), Lo, MacKinlay, and Zhang (2002), Boehmer, Saar, and Yu (2005), Hasbrouck and Saar (2007), Obizhaeva and Wang (2005))

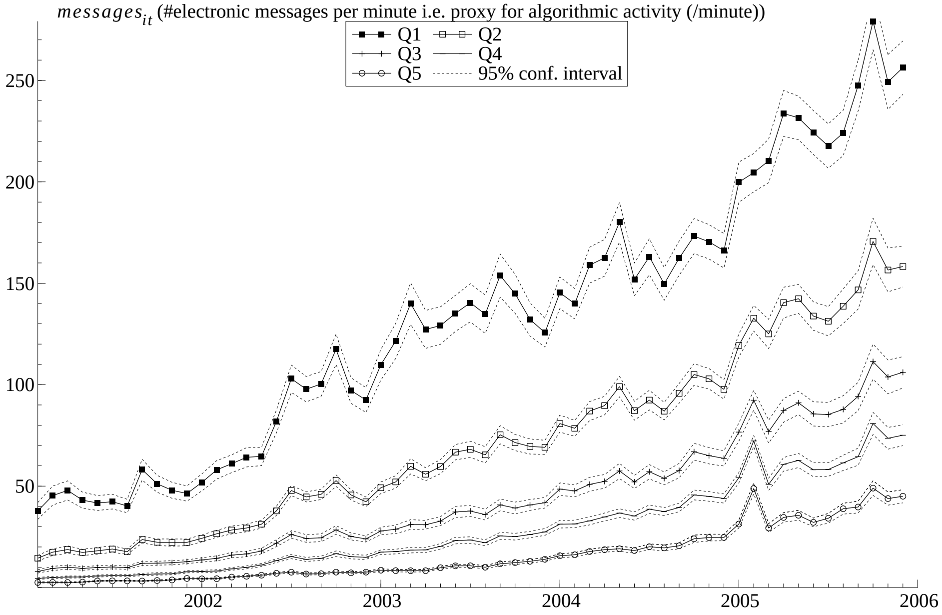
What do we do?

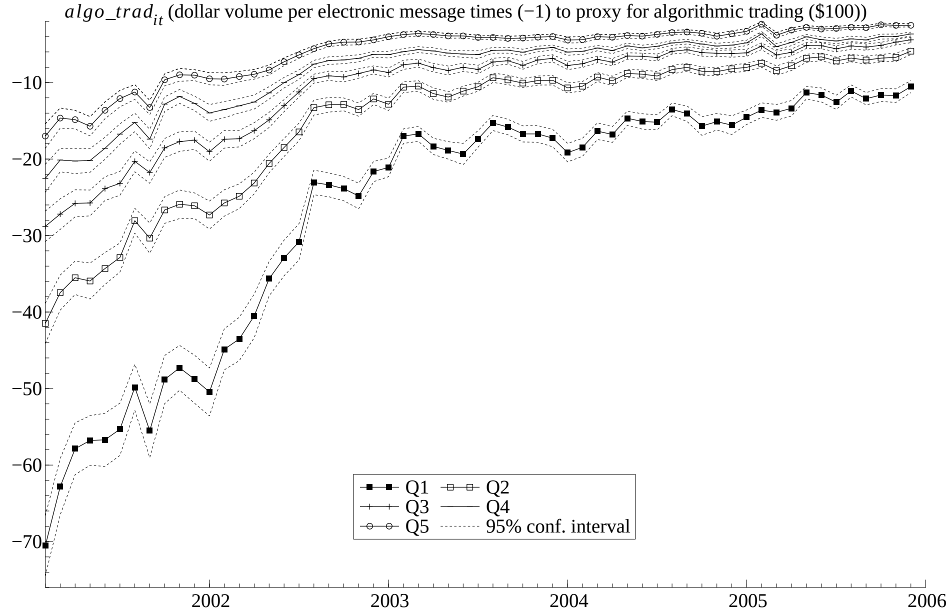
We measure algo trading through normalized (electronic) message traffic at the NYSE

- message traffic is electronic order submissions, cancels, and trade reports

Panel regressions associate time-series increases in algo trading with more liquid markets

- we exploit the exogenous, staggered introduction of autoquote at the NYSE as an instrument to establish causality


$messages_{it}$ (#electronic messages per minute i.e. proxy for algorithmic activity (/minute))
Q1
Q2
Q3
Q4
Q5
95% conf. interval
250
200
150
100
50
2002
2003
2004
2005
2006



$algo\_trad_{it}$ (dollar volume per electronic message times (−1) to proxy for algorithmic trading ($100))
−10
−20
−30
−40
−50
−60
−70
2002
2003
2004
2005
2006
Q1
Q2
Q3
Q4
Q5
95% conf. interval

Autoquote

Decimals in 2001 shrink inside quote depth

In October 2002 NYSE proposes "liquidity quote"

- firm bid and offer for substantial size ($> 15,000$ shares)

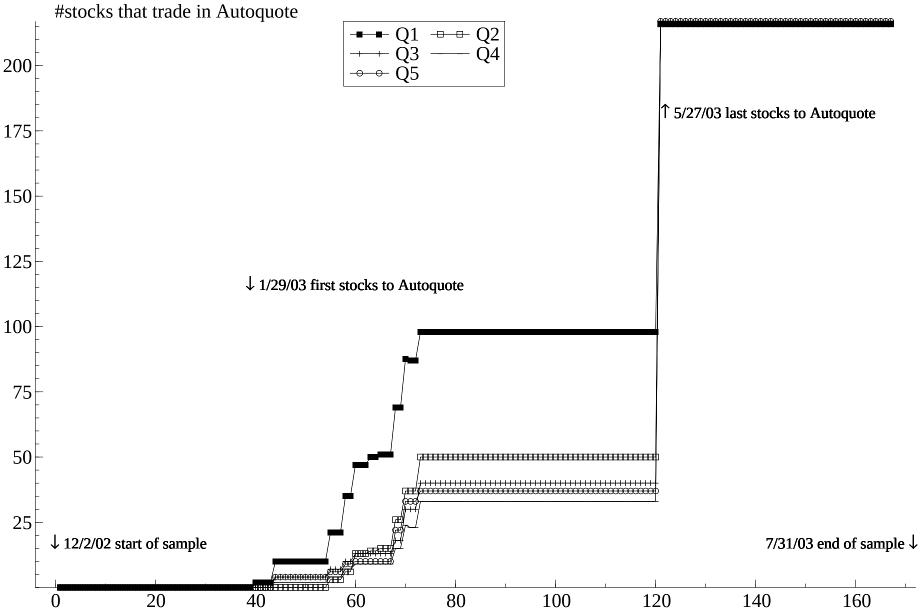
"Autoquote" is proposed simultaneously to free up the specialist to concentrate on the liquidity quote

- specialists had been manually disseminating the inside quote
- software would now "autoquote" any change to book

Liquidity quote delayed, autoquote immediate

Autoquote is important for AT

- immediate feedback about terms of trade
  - algo liquidity suppliers see abnormally wide inside quote
  - algo liquidity demanders access quote more quickly


#stocks that trade in Autoquote
Q1
Q2
Q3
Q4
Q5
↑ 5/27/03 last stocks to Autoquote
↓ 1/29/03 first stocks to Autoquote
↓ 12/2/02 start of sample
7/31/03 end of sample ↓
200
175
150
125
100
75
50
25
0
20
40
60
80
100
120
140
160

Autoquote dummy as instrument for $algo\_trad_{it}$

		$messa-ges_{it}$	$algo\_trad_{it}$	$share\_turnover_{it}$	$vola-tility_{it}$	$1/price_{it}$	$ln\_mar-ket\_cap_{it}$
Panel A: Overall, between, and within correlation after removing the time trend							
$auto\_quote_{it}$	ρ(overall)	0.15*	-0.05*	0.02*	0.03*	0.02*	0.10*
	ρ(between)	0.23*	-0.16*	0.06	0.09*	0.04	0.18*
	ρ(within)	0.08*	0.03*	-0.01*	0.00	0.01*	-0.01*
Panel B: Within correlation by quintile after removing the time trend							
$auto\_quote_{it}$ Q1	ρ(within)	0.15*	0.03*	0.01*	-0.00	0.03*	-0.03*
$auto\_quote_{it}$ Q2	ρ(within)	0.03*	0.04*	-0.01*	0.00	-0.02*	0.01*
$auto\_quote_{it}$ Q3	ρ(within)	0.05*	0.03*	0.00	-0.00	0.01	-0.02*
$auto\_quote_{it}$ Q4	ρ(within)	0.01*	0.00	-0.00	-0.00	-0.01	0.01
$auto\_quote_{it}$ Q5	ρ(within)	-0.00	0.03*	-0.02*	0.00	0.05*	-0.04*

[a]: Based on the time means i.e. $\overline{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$.

[b]: Based on the deviations from time means i.e. $x^*_{i,t} = x_{i,t} - \overline{x}_i$.

*: Significant at a 95% level.

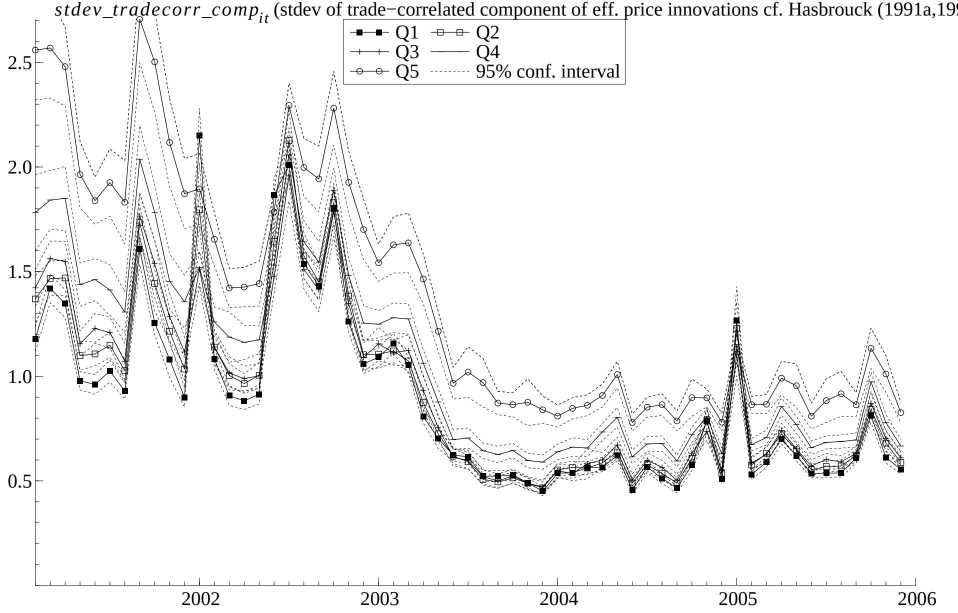
F-tests reject null that instruments do not enter first-stage regression for all our IV regressions

IV regression including T/O, volatility, price, and size

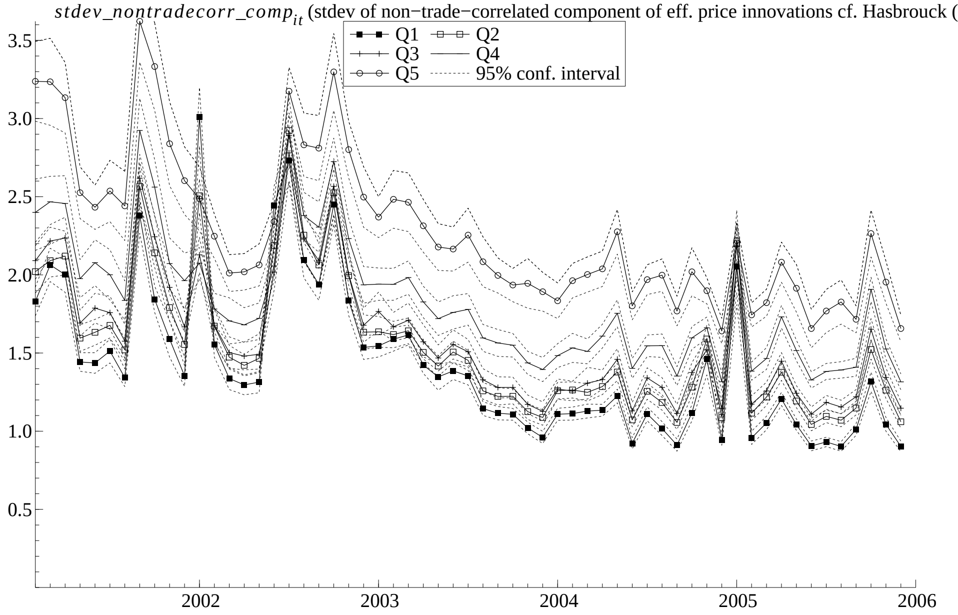
$$L_{it} = \alpha_i + \gamma_t + \beta A_{it} + \delta X_{it} + \varepsilon_{it}$$

	Coefficient on $algo\_trad_{it}$				
	Q1	Q2	Q3	Q4	Q5
Panel A: quoted spread, quoted depth, and effective spread					
$qspread_{it}$	-0.52**	-0.42**	-0.43	-0.16	9.92
	(-3.23)	(-2.21)	(-1.44)	(-0.05)	(1.22)
$qdepth_{it}$	-3.47**	-1.43	-1.99	15.49	0.61
	(-2.50)	(-1.16)	(-1.07)	(0.39)	(0.19)
$espread_{it}$	-0.18**	-0.32**	-0.35	-1.63	4.65
	(-2.65)	(-2.23)	(-1.56)	(-0.42)	(1.16)
Panel B: spread decompositions					
$rspread_{it}$	0.35**	0.76**	1.03**	14.26	15.88
	(3.53)	(3.97)	(2.06)	(0.46)	(1.36)
$adv\_selection_{it}$	-0.53**	-1.07**	-1.39**	-15.48	-11.21
	(-3.57)	(-4.08)	(-2.06)	(-0.47)	(-1.33)
#observations: 1082*167 (stock*day)					

*/**: Significant at a 95%/99% level.



$stdev\_tradecorr\_comp_{it}$ (stdev of trade−correlated component of eff. price innovations cf. Hasbrouck (1991a,19
Q1
Q2
Q3
Q4
Q5
95% conf. interval
2.5
2.0
1.5
1.0
0.5
2002
2003
2004
2005
2006



stdev_nontradecorr_comp_it (stdev of non−trade−correlated component of eff. price innovations cf. Hasbrouck (
Q1
Q2
Q3
Q4
Q5
95% conf. interval
3.5
3.0
2.5
2.0
1.5
1.0
0.5
2002
2003
2004
2005
2006

IV regression for LSB and Hasbrouck decompositions

$$M_{it} = \alpha_i + \gamma_t + \beta A_{it} + \delta X_{it} + \varepsilon_{it}$$

	Coefficient on $algo\_trad_{it}$				
	Q1	Q2	Q3	Q4	Q5
Panel A: Lin, Sanger, and Booth (1995)					
$LSB95\_fixed_{it}$	0.26**	0.59**	0.69**	9.91	8.97
	(3.63)	(4.16)	(2.26)	(0.46)	(1.36)
$LSB95\_adv\_sel_{it}$	-0.26**	-0.61**	-0.84**	-12.19	-7.72
	(-3.46)	(-3.80)	(-2.14)	(-0.46)	(-1.32)
$LSB95\_order\_persist_{it}$	-0.18**	-0.30**	-0.21	0.66	3.30
	(-3.06)	(-3.10)	(-1.60)	(0.28)	(1.21)
Panel B: "Hasbrouck decomposition"					
$stdev\_tradecorr\_comp_{it}$	-0.22**	-0.26**	-0.30*	-3.39	-0.57**
	(-2.62)	(-3.08)	(-1.69)	(-0.30)	(-2.73)
$stdev\_nontradecorr\_comp_{it}$	0.13**	0.13**	0.13	1.03	0.13
	(2.48)	(2.36)	(1.47)	(0.28)	(1.12)
#observations: 1082*167 (stock*day)					

*/**: Significant at a 95%/99% level.

Interpretation: generalized Roll model

i.i.d. innovation in efficient price in each of two periods,
$m_t = m_{t-1} + w_t$, with $w_t \in \{-\varepsilon, +\varepsilon\}$ equally likely

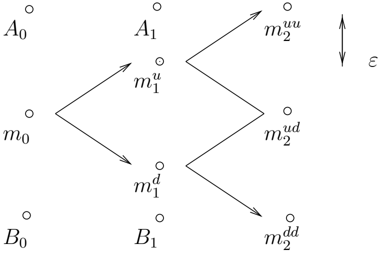
1. At $t = 0$, risk-neutral humans submit a bid and ask quote and, given full competition, the first one arriving bids her reservation price.
2. At $t = 1$, humans can buy the information w_1 at cost c. If bought, they can submit a new limit order.
3. At $t = 2$, two informed liquidity demanders arrive, one with a positive private value associated with a trade, $+\theta$, the other with a negative private value, $-\theta$.

Assume

1. $2c > \theta$ i.e. cost of "observing" for humans is sufficiently high ("quotes become stale")
2. $\varepsilon > \theta$ i.e. large innovations prevent simultaneous transaction by both liquidity demanders (unimportant)

Interpretation: generalized Roll model (ctd)

Humans only

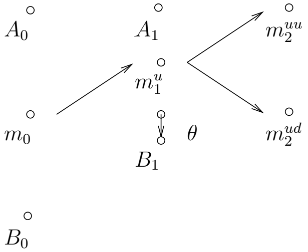


probability	state	efficient price	transaction price
.25	uu	m_2^{uu}	m_2^{uu}
.50	ud and du	$m_2^{ud} = m_2^{du}$	no transaction
.25	dd	m_2^{dd}	m_2^{dd}

- at $t = 1$ public information does not enter quotes
- "welfare loss" due to possible unrealized private value

Interpretation: generalized Roll model (ctd)

Introduce an algo that buys information at zero cost



probability	state	efficient price	transaction price
.25	uu	m_2^{uu}	m_2^{uu}
.25	ud	$m_2^{ud} = m_2^{du}$	$m_2^{ud} - \theta$
.50	du	$m_2^{du} = m_2^{ud}$	$m_2^{du} + \theta$
.25	dd	m_2^{dd}	m_2^{dd}

- at $t = 1$ public information enters quotes, but midquote becomes “noisy” measure of true value
- no unrealized private value

Interpretation: generalized Roll model (ctd)

Efficient price is revealed without trades i.e. public information enters quotes without trades

Revenue to liquidity suppliers is positive

Also matches other findings: more frequent trades, narrower quotes

Note: model assumes that algo competition is less intense that human competition

Conclusion

1. Panel regressions time-series increases in algo trading correlate with liquidity improvement
2. Staggered introduction of structural change (autoquote) as an instrument confirms algo trading lowers trading cost and increases price informativeness
3. Surprisingly, revenues to liquidity suppliers increase with algo trading. Market power for some period after introduction?

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Almgren, R. and N. Chriss (2000).
Optimal execution of portfolio transactions.
Journal of Risk 3, 5–39.

Bertsimas, D. and A. Lo (1998).
Optimal control of execution costs.
Journal of Financial Markets 1, 1–50.

Biais, B., D. Martimort, and J. Rochet (2000).
Competing mechanisms in a common value environment.
Econometrica 68, 799–837.

Boehmer, E., G. Saar, and L. Yu (2005).
Lifting the veil: An analysis of pre-trade transparency at the nyse.
Journal of Finance 60, 783–815.

Copeland, T. and D. Galai (1983).
Information effects on the bid-ask spread.
Journal of Finance 38, 1457–1469.

Foucault, T., A. Roëll, and P. Sandas (2003).
Market making with costly monitoring: An analysis of the soes controversy.
Review of Financial Studies 16, 345–384.

Griffiths, M., B. Smith, D. Turnbull, and R. White (2000).
The costs and determinants of order aggressiveness.
Journal of Financial Economics 56, 65–88.

Harris, L. (1998).
Optimal dynamic order submission strategies in some stylized trading problems.
Financial Markets, Institutions, and Instruments 7, 1–76.

Hasbrouck, J. (1991a).
Measuring the information content of stock trades.
Journal of Finance 46, 179–207.

Hasbrouck, J. (1991b).
The summary informativeness of stock trades: An econometric analysis.
Review of Financial Studies 4, 571–595.

Hasbrouck, J. and G. Saar (2007).
Technology and liquidity provision: The blurring of traditional definitions.
Technical report, New York University.

Keim, D. and A. Madhavan (1995).
Anatomy of the trading process: Empirical evidence on the behavior of institutional traders.
Journal of Financial Economics 37, 371–398.

Kyle, A. (1985).
Continuous auctions and insider trading.
Econometrica 53, 1315–1335.

Lin, J., G. Sanger, and G. Booth (1995).
Trade size and components of the bid-ask spread.
Review of Financial Studies 8, 1153–1183.

Lo, W., A. MacKinlay, and J. Zhang (2002).
Econometric models of limit-order executions.
Journal of Financial Economics 65, 31–71.

Obizhaeva, A. and J. Wang (2005).
Optimal trading strategy and supply/demand dynamics.
Technical report, MIT.

Rock, K. (1990).
The specialist's order book and price anomalies.
Technical report, Harvard University.