# Supplemental Appendix

# The Value of Software

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# Appendix A Additional Figures and Tables

Table A.1. List of Sub-Industries Used to Identify Software Companies

RBICS industry name		
Asset Management Software Automotive Enterprise Management Software	Government and Public Service Industry Software Handheld and Smart Phone Games Software	Other Games Software Other Handheld and Smart Phone Software
Automotive Industry Software	Healthcare Management Software	Other Healthcare and Pharma Industry Software
Business Intelligence Software	Healthcare Operations Support Software	Other Network Software
Business Planning and Control ERP Software	Home and Office Multimedia Software	Other Telecommunications Industry Software
Commercial Bank and Credit Union Software	Hospitality Industry Software	Patient Data Management Software
Communications Infrastructure Software	Human Resources ERP Software	Payment Processing Software
Computer Aided Design (CAD) Software	IC-Level Electronic Design Software	Print and Prepress Industry Software
Computer and Software Stores	IC-Level Intellectual Property Software Libraries	Productivity Software
Console Games Software	Insurance Software	Real Estate and Construction Industry Software
Customer Service Software	Investment Management/Brokerage Software	Retail Industry Software
Data Storage Infrastructure Software	Legal, Tax and Accounting Industry Software	Sales Force Automation (SFA) Software
Diversified Content Management Software	Manufacturing Industry Software	Software Design and Engineering Consulting
Diversified Customer Relationship Software	Mapping/Geographic Information Systems Software Software Software	Software Development Software
Diversified Enterprise Resource Planning Software	g Software   Marketing CRM Software	Software Distributors
Diversified IT Infrastructure Software	Media and Entertainment Industry Software	Supply Chain ERP Software
Document Management Software	Mobile Platform Applications Software	Telecommunications Customer Relationship Software
Drug Development Software	Multi-Type Home and Office Software	Telecommunications Operations Support Software
E-Signature Software	Multimedia Design and Engineering Software	Trading Software
Educational Software	Multiple Industry-Specific Software	Transportation Industry Software
Embedded Automotive Software	Network Administration Software	Utilities Industry Software
Energy Industry Software	Network Security Access Policy Software	Vehicle Autonomous Control Software
Enhanced Telecommunications Services Software	Network Security Software	Virtual Reality Design and Engineering Software
Enterprise Middleware Software	Not-For-Profit Industry Software	Web Development Software Makers
Enterprise Security Management Software	Online Game Websites and Software	Web Navigation Sites and Software
Financial and Compliance ERP Software	Operating Systems Software	Web Portal Sites and Software
General Enterprise Management Software	Other Design and Engineering Software	Web Search Sites and Software
General and Mixed-Type Software	Other Finance Industry Software	
General and Mixed-Type Software	Other Finance Industry Software	

Notes: This table lists each of the FactSet Revere Business Industry Classification System (RBICS) sub-industries used in our sample construction. We select all sub-industries containing the word software and for which the main business relates to creating and selling software or software platforms. There are 1,207 total firms spanning 83 distinct RBICS sub-industries.

Table A.2. Largest Software Companies

	Market cap.	Cumulative marke	t share relative to			Market Cap	Cumulative marke	t share relative to
Year Name	(billions)	Softw. market cap.	Total market cap.	Year	Name	(billions)	Softw. market cap.	Total market cap.
1996 Microsoft Corp	98.98	47.95	1.16	1997	Microsoft Corp	156.00	54.88	1.41
1996 CA Inc	18.15	56.74	1.37	1997	CA Inc	28.98	65.07	1.67
1996 PTC Inc	6.55	59.91	1.45	1997	Peoplesoft Inc.	8.73	68.14	1.75
1996 Peoplesoft Inc.	5.16	62.41	1.51	1997	BMC Software Inc	6.74	70.51	1.81
1996 Netscape Communications Corp	5.00	64.83	1.57	1997	PTC Inc	6.05	72.64	1.86
1996 BMC Software Inc	4.18	66.86	1.62	1997	McAfee Inc	3.70	73.94	1.89
1996 Cadence Design Systems Inc	3.27	68.44	1.66	1997	Altaba Inc	3.12	75.04	1.92
1996 Novell Inc.	3.26	70.02	1.70	1997	Adobe Inc	2.84	76.04	1.95
1996 Ascential Software Corp	3.07	71.51	1.73	1997	Edwards J D & Co	2.74	77.00	1.97
1996 Adobe Inc	2.67	72.80	1.76	1997	SunGard Data Systems Inc	2.68	77.94	2.00
1998 Microsoft Corp	342.56	63.53	2.52	1999	Microsoft Corp	602.43	48.74	3.42
1998 Altaba Inc	23.38	67.87	2.69	1999	Altaba Inc	115.27	58.07	4.07
1998 CA Inc	22.94	72.12	2.86	1999	CA Inc	37.70	61.12	4.28
1998 BMC Software Inc	9.67	73.92	2.93	1999	VERITAS Software Co	37.09	64.12	4.49
1998 McAfee Inc	9.15	75.61	3.00	1999	Ariba Inc	32.60	66.76	4.68
1998 Cadence Design Systems Inc	6.60	76.84	3.05	1999	BMC Software Inc	19.37	68.33	4.79
1998 Novell Inc.	6.12	77.97	3.09	1999	Siebel Systems Inc	15.53	69.58	4.88
1998 Netscape Communications Corp	6.05	79.09	3.14	1999	I2 Technologies Inc	15.00	70.80	4.96
1998 Peoplesoft Inc.	4.51	79.93	3.17	1999	Compuware Corp	13.33	71.88	5.04
1998 PTC Inc	4.34	80.73	3.20	1999	Novell Inc.	13.04	72.93	5.11
					Table A.2 – continues in	the next page		

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Year Name	(billions)	Softw. market cap.	Total market cap.	Year	Name	(billions)	Softw. market cap.	Total market cap
2000 Microsoft Corp	231.29	37.23	1.43	2001	Microsoft Corp	357.95	59.12	2.51
2000 VERITAS Software Co	34.38	42.76	1.65	2001	CA Inc	19.87	62.40	2.65
2000 Siebel Systems Inc	29.92	47.58	1.83	2001	VERITAS Software Co	18.13	65.39	2.78
2000 Bea Systems Inc	25.88	51.74	1.99	2001	Siebel Systems Inc	13.07	67.55	2.87
2000 I2 Technologies Inc	22.07	55.30	2.13	2001	Peoplesoft Inc.	12.29	69.58	2.96
2000 Altaba Inc	16.88	58.01	2.23	2001	Altaba Inc	10.21	71.27	3.03
2000 Adobe Inc	14.02	60.27	2.32	2001	Intuit Inc.	9.07	72.76	3.09
2000 Ariba Inc	13.54	62.45	2.41	2001	SunGard Data Systems Inc	8.08	74.10	3.15
2000 CA Inc	11.56	64.31	2.48	2001	Adobe Inc	7.33	75.31	3.20
2000 Peoplesoft Inc.	10.70	66.03	2.54	2001	Bea Systems Inc	6.18	76.33	3.24
2002 Microsoft Corp	276.63	58.51	2.44	2003	Microsoft Corp	295.29	46.67	1.97
2002 Oracle Corp	56.91	70.55	2.95	2003	Oracle Corp	69.16	57.60	2.43
2002 Altaba Inc	9.73	72.60	3.03	2003	Altaba Inc	29.75	62.30	2.63
2002 Intuit Inc.	9.63	74.64	3.12	2003	VERITAS Software Co	15.88	64.82	2.73
2002 CA Inc	7.74	76.28	3.19	2003	CA Inc	15.83	67.32	2.84
2002 SunGard Data Systems Inc	6.67	77.69	3.24	2003	Intuit Inc.	10.49	68.98	2.91
2002 VERITAS Software Co	6.44	79.05	3.30	2003	Adobe Inc	9.31	70.45	2.97
2002 Peoplesoft Inc.	5.74	80.26	3.35	2003	Peoplesoft Inc.	8.20	71.74	3.02
2002 Adobe Inc	5.73	81.48	3.40	2003	SunGard Data Systems Inc	7.91	72.99	3.08
2002 Bea Systems Inc	4.71	82.47	3.44	2003	Siebel Systems Inc	6.94	74.09	3.12
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Year Name	(billions)	Softw. market cap.	Total market cap.	Year Name	(billions)	Softw. market cap.	Total market cap
2004 Microsoft Corp	290.72	41.04	1.71	2005 Microsoft Corp	270.22	36.44	1.50
2004 Oracle Corp	71.69	51.15	2.14	2005 Alphabet Inc	82.76	47.60	1.96
2004 Altaba Inc	52.13	58.51	2.44	2005 Oracle Corp	63.03	56.10	2.31
2004 Electronic Arts Inc	18.93	61.19	2.56	2005 Altaba Inc	56.03	63.65	2.62
2004 Alphabet Inc	18.42	63.79	2.67	2005 Adobe Inc	21.86	66.60	2.74
2004 CA Inc	18.19	66.35	2.77	2005 Gen Digital Inc	18.24	69.06	2.85
2004 Adobe Inc	15.32	68.52	2.86	2005 CA Inc	16.32	71.26	2.94
2004 VERITAS Software Co	12.08	70.22	2.93	2005 Electronic Arts Inc	15.85	73.40	3.02
2004 Peoplesoft Inc.	9.95	71.63	2.99	2005 SunGard Data Systems	Inc 10.44	74.86	3.08
2004 Autodesk Inc	8.71	72.86	3.04	2005 VERITAS Software Co	10.43	76.40	3.14
2006 Microsoft Corp	291.94	36.61	1.43	2007 Microsoft Corp	332.11	34.33	1.60
2006 Alphabet Inc	104.84	49.75	1.95	2007 Alphabet Inc	163.26	51.20	2.38
2006 Oracle Corp	88.82	60.89	2.39	2007 Oracle Corp	115.98	63.19	2.94
2006 Altaba Inc	34.74	65.25	2.56	2007 Altaba Inc	31.10	66.41	3.09
2006 Adobe Inc	24.20	68.28	2.68	2007 Adobe Inc	24.31	68.92	3.20
2006 Gen Digital Inc	19.34	70.71	2.77	2007 Electronic Arts Inc	18.52	70.83	3.29
2006 Electronic Arts Inc	15.61	72.66	2.85	2007 Gen Digital Inc	13.64	72.24	3.36
2006 CA Inc	11.87	74.15	2.91	2007 CA Inc	12.86	73.57	3.42
2006 Intuit Inc.	10.64	75.49	2.96	2007 Autodesk Inc	11.49	74.76	3.48
2006 Autodesk Inc	9.36	76.66	3.00	2007 Intuit Inc.	10.52	75.85	3.53
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Year Name	(billions)	Softw. market cap.	Total market cap.	Year Name	(billions)	Softw. market cap.	Total market cap
2008 Microsoft Corp	172.80	32.33	1.41	2009 Microsoft Corp	268.56	32.14	1.70
2008 Oracle Corp	89.47	49.07	2.14	2009 Alphabet Inc	151.03	50.21	2.66
2008 Alphabet Inc	73.86	62.89	2.75	2009 Oracle Corp	122.93	64.92	3.44
2008 Altaba Inc	16.98	66.07	2.89	2009 Altaba Inc	23.59	67.75	3.59
2008 Gen Digital Inc	11.30	68.18	2.98	2009 Adobe Inc	19.22	70.05	3.71
2008 Activision Blizzard Inc	11.23	70.28	3.07	2009 Gen Digital Inc	14.42	71.77	3.80
2008 Adobe Inc	11.20	72.38	3.16	2009 Activision Blizzard Inc	13.89	73.44	3.89
2008 CA Inc	9.53	74.16	3.24	2009 CA Inc	11.57	74.82	3.97
2008 Bea Systems Inc	7.93	75.19	3.28	2009 Baidu Inc	10.82	76.12	4.03
2008 Intuit Inc.	7.61	76.61	3.34	2009 Intuit Inc.	9.73	77.28	4.10
2010 Microsoft Corp	234.53	25.73	1.28	2011 Microsoft Corp	217.82	24.80	1.24
2010 Oracle Corp	158.14	43.07	2.15	2011 Alphabet Inc	167.85	43.92	2.19
2010 Alphabet Inc	144.70	58.95	2.94	2011 Oracle Corp	128.91	58.60	2.93
2010 Baidu Inc	26.18	61.82	3.08	2011 Baidu Inc	31.59	62.19	3.10
2010 Altaba Inc	21.77	64.21	3.20	2011 Altaba Inc	19.58	64.42	3.22
2010 Salesforce Inc	17.34	66.11	3.30	2011 Intuit Inc.	15.63	66.20	3.30
2010 Adobe Inc	15.45	67.80	3.38	2011 Activision Blizzard Inc	13.96	67.79	3.38
2010 Intuit Inc.	15.31	69.48	3.46	2011 Adobe Inc	13.90	69.37	3.46
2010 Activision Blizzard Inc	14.72	71.10	3.54	2011 Salesforce Inc	13.80	70.95	3.54
2010 Citrix Systems Inc	12.83	72.50	3.61	2011 Gen Digital Inc	11.42	72.25	3.61
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	Market cap.	Cumulative market	et share relative to		Market Cap	Cumulative marke	et share relative to
Year Name	(billions)	Softw. market cap.	Total market cap.	Year Name	(billions)	Softw. market cap.	Total market cap.
2012 Microsoft Corp	223.67	23.18	1.13	2013 Alphabet Inc	313.04	22.78	1.22
2012 Alphabet Inc	189.19	42.79	2.08	2013 Microsoft Corp	310.50	45.38	2.44
2012 Oracle Corp	157.75	59.13	2.88	2013 Oracle Corp	172.07	57.90	3.11
2012 Baidu Inc	27.54	61.99	3.02	2013 Baidu Inc	49.07	61.47	3.30
2012 Salesforce Inc	23.87	64.46	3.14	2013 Altaba Inc	41.02	64.46	3.46
2012 Altaba Inc	22.19	66.76	3.25	2013 Salesforce Inc	33.28	66.88	3.59
2012 Adobe Inc	18.62	68.69	3.35	2013 Adobe Inc	29.72	69.04	3.71
2012 Intuit Inc.	17.61	70.52	3.43	2013 Intuit Inc.	21.74	70.62	3.79
2012 Cerner Corp	13.34	71.90	3.50	2013 Cerner Corp	19.16	72.02	3.87
2012 Gen Digital Inc	12.97	73.24	3.57	2013 Gen Digital Inc	16.31	73.20	3.93
2014 Microsoft Corp	381.73	23.73	1.36	2015 Alphabet Inc	489.26	26.37	1.84
2014 Alphabet Inc	331.25	44.32	2.54	2015 Microsoft Corp	439.68	50.06	3.50
2014 Oracle Corp	197.48	56.59	3.25	2015 Oracle Corp	153.47	58.33	4.08
2014 Baidu Inc	63.16	60.52	3.47	2015 Alibaba Group Holding L	td 81.06	62.70	4.39
2014 Alibaba Group Holding Ltd	51.77	63.74	3.66	2015 Salesforce Inc	52.06	65.51	4.58
2014 Altaba Inc	47.32	66.68	3.83	2015 Baidu Inc	51.23	68.27	4.77
2014 Salesforce Inc	37.42	69.00	3.96	2015 Adobe Inc	46.76	70.79	4.95
2014 Adobe Inc	36.17	71.25	4.09	2015 Altaba Inc	31.56	72.49	5.07
2014 Intuit Inc.	26.32	72.89	4.18	2015 Activision Blizzard Inc	28.43	74.02	5.18
2014 Cerner Corp	22.08	74.26	4.26	2015 Intuit Inc.	25.48	75.39	5.27
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Year Name	(billions)	Softw. market cap.	Total market cap.	Year Name	(billions)	Softw. market cap.	Total market cap
2016 Alphabet Inc	503.07	27.52	1.75	2017 Alphabet Inc	679.96	26.86	1.99
2016 Microsoft Corp	480.34	53.80	3.42	2017 Microsoft Corp	659.09	52.89	3.92
2016 Oracle Corp	157.74	62.43	3.97	2017 Oracle Corp	195.72	60.62	4.49
2016 Alibaba Group Holding Ltd	115.07	68.28	4.38	2017 Adobe Inc	86.09	64.02	4.74
2016 Adobe Inc	50.88	71.06	4.56	2017 Salesforce Inc	73.84	66.94	4.96
2016 Salesforce Inc	46.49	73.60	4.72	2017 Baidu Inc	65.75	69.54	5.15
2016 Baidu Inc	45.24	76.08	4.88	2017 Altaba Inc	48.22	71.66	5.31
2016 Altaba Inc	36.94	78.10	5.01	2017 Activision Blizzard Inc	47.97	73.55	5.45
2016 Intuit Inc.	29.42	79.71	5.11	2017 Intuit Inc.	40.34	75.15	5.57
2016 Activision Blizzard Inc	26.92	81.18	5.20	2017 Electronic Arts Inc	32.25	76.42	5.66
2018 Microsoft Corp	780.36	28.83	2.52	2019 Microsoft Corp	1200.25	31.50	3.06
2018 Alphabet Inc	674.83	53.76	4.69	2019 Alphabet Inc	858.94	54.05	5.25
2018 Oracle Corp	162.04	59.74	5.21	2019 Oracle Corp	169.94	58.51	5.69
2018 Adobe Inc	110.33	63.82	5.57	2019 Adobe Inc	159.08	62.68	6.09
2018 Salesforce Inc	104.78	67.69	5.91	2019 Salesforce Inc	144.26	66.47	6.46
2018 Intuit Inc.	51.08	69.58	6.07	2019 Intuit Inc.	68.18	68.26	6.64
2018 Baidu Inc	44.20	71.21	6.21	2019 ServiceNow Inc	53.25	69.65	6.77
2018 Activision Blizzard Inc	35.55	72.52	6.33	2019 Activision Blizzard Inc	45.68	70.85	6.89
2018 ServiceNow Inc	31.92	73.70	6.43	2019 Shopify Inc	41.21	71.93	6.99
2018 Roper Technologies Inc	28.29	74.73	6.51	2019 Autodesk Inc	40.29	72.99	7.10
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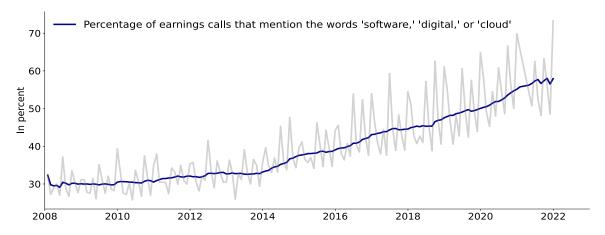
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	Market cap.	Cumulative marke	t share relative to			Market Cap	Cumulative marke	et share relative to
Year Name	(billions)	Softw. market cap.	Total market cap.	Year	Name	(billions)	Softw. market cap.	Total market cap
2020 Microsoft Corp	1678.38	28.00	3.54	2021	Microsoft Corp	2525.08	30.92	4.28
2020 Alphabet Inc	1102.83	46.40	5.87	2021	Alphabet Inc	1787.70	52.81	7.31
2020 Adobe Inc	239.56	50.39	6.38	2021	Adobe Inc	269.35	56.11	7.77
2020 Salesforce Inc	203.61	53.79	6.81	2021	Salesforce Inc	250.32	59.18	8.19
2020 Oracle Corp	190.45	56.97	7.21	2021	Oracle Corp	232.89	62.03	8.59
2020 Shopify Inc	124.56	59.04	7.47	2021	Intuit Inc.	182.14	64.26	8.90
2020 ServiceNow Inc	107.39	60.84	7.70	2021	Shopify Inc	156.52	66.17	9.16
2020 Intuit Inc.	99.80	62.50	7.91	2021	ServiceNow Inc	129.17	67.76	9.38
2020 Block Inc	83.53	63.89	8.08	2021	Snowflake Inc	103.76	69.03	9.56
2020 Activision Blizzard Inc	71.89	65.09	8.24	2021	Snap Inc	63.75	69.81	9.66
2022 Microsoft Corp	1785.94	35.88	3.89	2023	Microsoft Corp	2794.83	39.51	5.01
2022 Alphabet Inc	1055.04	57.08	6.19	2023	Alphabet Inc	1626.06	62.50	7.93
2022 Oracle Corp	220.39	61.51	6.68	2023	Adobe Inc	271.45	66.33	8.41
2022 Adobe Inc	155.48	64.63	7.01	2023	Oracle Corp	255.73	70.65	8.93
2022 Salesforce Inc	132.59	67.29	7.30	2023	Salesforce Inc	254.72	74.25	9.39
2022 Shopify Inc	109.57	68.78	7.50	2023	Intuit Inc.	174.97	76.72	9.70
2022 Intuit Inc.	109.34	70.98	7.74	2023	ServiceNow Inc	144.83	78.77	9.96
2022 ServiceNow Inc	78.59	72.56	7.91	2023	Synopsys Inc	78.26	79.87	10.10
2022 Activision Blizzard Inc	60.03	73.77	8.04	2023	Cadence Design Systems Inc	74.00	80.92	10.24
2022 VMware Inc	52.23	74.81	8.16	2023	Activision Blizzard Inc	73.67	82.10	10.38

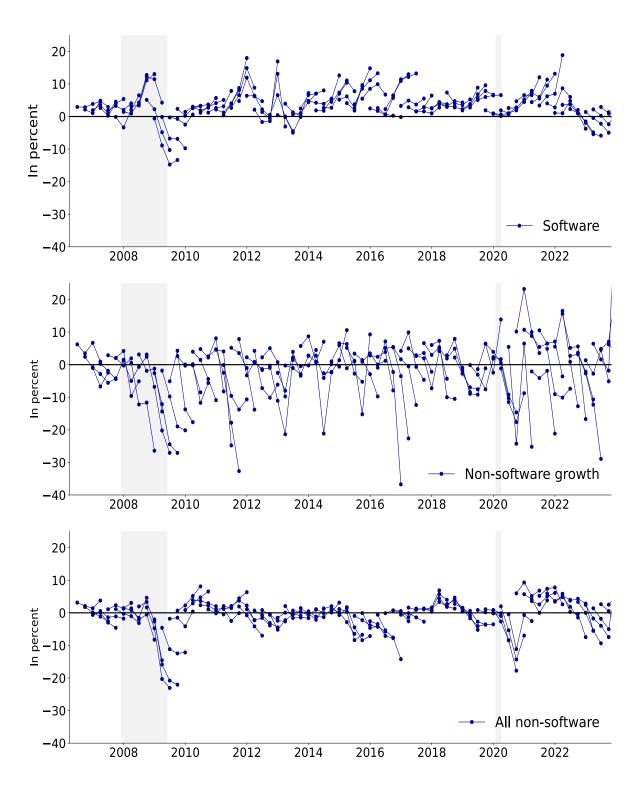
Notes: This table lists the ten largest software companies by market capitalization for each year from 1996 to 2023 as well as the cumulative market share relative to the market capitalization of all software companies and relative to the total market capitalization.

Fig. A.1. Software Mentions in Earnings Calls



Notes: This figure shows the percentage of earnings calls that mention at least one of the following words: software, digital, or cloud. We present average values at both quarterly (gray line) and yearly (blue line) frequencies. The figure spans the period from January 2008 through February 2022.

Fig. A.2. Biases in Analysts' Forecasts: Post 2006



Notes: This figure shows the average forecast bias for every quarter in our sample for software companies, non-software growth companies, and all non-software companies. Each line in the figure represents the average forecast error across the current quarter and the subsequent three quarters, while NBER recession dates are indicated by gray shaded bars. The sample spans from 2006Q1 to 2023Q3.

Table A.3. Summary Statistics: Biases in Analysts' Forecasts

A: Software comp	oanies			
		Forecast horiz	zon in quarters	
	1	2	3	4
Mean	2.21	1.78	2.21	2.94
$t ext{-}statistic$	[6.88]	[2.69]	[2.16]	[2.06]
std	20.51	39.33	55.27	73.10
5%	-8.59	-20.90	-31.19	-38.79
25%	-0.25	-3.23	-5.91	-7.84
50%	1.78	1.45	0.93	0.60
75%	4.65	6.15	7.43	8.78
95%	13.06	20.90	28.26	37.53
Observations	13,417	12,893	$12,\!243$	11,604 1
B: All non-softwa	re companies			
			zon in quarters	
	1	2	3	4
Mean	1.54	0.03	-1.41	-2.25
$t ext{-}statistic$	[7.15]	[0.08]	[-2.36]	[-2.98]
std	35.69	62.30	92.90	119.26
5%	-15.07	-27.37	-36.90	-43.39
25%	-2.15	-5.06	-7.42	-9.34
50%	0.81	0.25	-0.22	-0.55
75%	4.34	5.63	6.81	8.01
95%	18.78	27.15	35.71	43.48
Observations	212,216	202,813	189,954	178,155
C: Non-software g	growth companies			
			zon in quarters	
	1	2	3	4
Mean	2.41	-0.24	-4.64	-8.09
$t ext{-}statistic$	[6.07]	[-0.29]	[-3.71]	[-4.54]
std	45.08	86.90	130.82	169.30
5%	-16.62	-35.00	-53.45	-66.53
25%	-1.62	-4.97	-7.98	-10.55
50%	1.08	0.50	-0.07	-0.56
75%	4.55	5.93	6.98	7.83
95%	20.61	30.87	40.40	46.81
Observations	26,329	$25,\!375$	23,994	22,637

Notes: This table presents summary statistics of forecast errors for software companies, all non-software companies, and non-software growth companies. The sample spans from 1996Q1 to 2023Q3.

Table A.4. Biases in Analysts' Forecasts: Robustness to the Measure of Consensus

		Forecast horizon in quarters						
Coef	Variable	1	2	3	4			
A: Using the me	edian forecast as	the measure	of consensus					
a	1	2.21	1.78	2.21	2.94			
$t ext{-}statistic$		[6.88]	[2.69]	[2.16]	[2.06]			
Observations		13,417	12,893	12,243	11,604			
B: Using the me	an forecast as t	he measure o	f consensus					
a	1	2.02	1.50	2.07	2.77			
t- $statistic$		[5.84]	[2.14]	[2.03]	[1.95]			
Observations		13,418	12,894	12,243	11,604			

Notes: This table presents the average forecast error for software companies using either the median forecast among analysts as the measure of consensus (Panel A) or the mean forecast (Panel B). The t-statistics, calculated using standard errors clustered by both firm and year-quarter, are included in square brackets. All forecast errors are presented as percentages. The sample spans from 1996Q1 to 2023Q3.

Table A.5. Biases in Analysts' Forecasts: Subsample Analysis

Sample of softw	vare companies				
		Fo	orecast horiz	on in quarte	rs
Coef	Variable	1	2	3	4
A: Full sample	period: 1996 to	2023			
a	1	2.21	1.78	2.21	2.94
$t ext{-}statistic$		[6.88]	[2.69]	[2.16]	[2.06]
Observations		$13,\!417$	12,893	12,243	11,60
B: Sample perio	od: 1996 to 200	5			
a	1	0.28	-2.26	-3.05	-5.13
$t ext{-}statistic$		[0.27]	[-1.18]	[-0.98]	[-1.20]
Observations		2,871	2,750	2,630	2,462
C: Sample perio	od: 2006 to 201	5			
a	1	2.51	2.79	3.79	5.41
$t ext{-}statistic$		[6.56]	[3.00]	[2.65]	[2.80]
Observations		5,021	4,918	4,751	4,605
D: Sample peri	od: 2016 to 202	3			
a	1	2.94	2.96	3.51	4.82
$t ext{-}statistic$		[8.80]	[4.07]	[3.04]	[2.82]
Observations		5,525	$5,\!225$	4,862	4,537

Notes: This table presents the average forecast error for software companies across various subperiods. Panel A details results for the entire 28-year span from 1996 to 2023. Panels B, C, and D focus on the intervals 1996-2005, 2006-2015, and 2016-2023, respectively. We include t-statistics in square brackets, calculated using standard errors that are clustered by both firm and year-quarter. All forecast errors are presented as percentages.

Table A.6. Biases in Analysts' Forecasts: Robustness No Winsorization

Sample of softw	are companies							
		Forecast horizon in quarters						
Coef	Variable	1	2	3	4			
A: Sample perio	od: 1996 to 202	23						
a	1	3.33	2.34	4.63	6.42			
$t ext{-}statistic$		[3.03]	[2.49]	[2.70]	[2.05]			
Observations		13,421	12,898	12,249	11,608			
B: Sample perio	od: 1996 to 200	)5						
a	1	5.40	0.82	5.65	6.07			
$t ext{-}statistic$		[1.07]	[0.26]	[0.86]	[0.48]			
Observations		2,873	2,752	2,634	2,463			
C: Sample perio	od: 2006 to 202	23						
a	1	2.76	2.75	4.34	6.51			
$t ext{-}statistic$		[10.14]	[3.41]	[3.54]	[3.19]			
Observations		10,548	10,146	9,615	9,145			

Notes: This table presents the average forecast error for software companies when we do not winsorize outliers. We present results across various subperiods. Panel A details results for the entire 28-year span from 1996 to 2023. Panels B and C focus on the intervals 1996-2005, 2006-2023, respectively. We include t-statistics in square brackets, calculated using standard errors that are clustered by both firm and year-quarter. All forecast errors are presented as percentages.

Table A.7. Biases in Analysts' Forecasts: Robustness Winsorize Outliers at the 99% Level in Absolute Value

Sample of software companies								
		Forecast horizon in quarters						
Coef	Variable	1	2	3	4			
A: Sample period: 1996 to 2023								
a	1	2.07	1.28	0.61	0.49			
$t ext{-}statistic$		[8.95]	[2.71]	[0.89]	[0.52]			
Observations		13,384	12,855	12,198	11,546			
B: Sample perio	od: 1996 to 200	)5						
a	1	1.16	-1.21	-2.72	-4.90			
$t ext{-}statistic$		[1.60]	[-0.84]	[-1.18]	[-1.50]			
Observations		2,863	2,738	2,616	2,442			
C: Sample perio	od: 2006 to 202	23						
a	1	2.32	1.95	1.52	1.93			
$t ext{-}statistic$		[11.59]	[4.84]	[2.68]	[2.57]			
Observations		10,521	10,117	9,582	9,104			

Notes: This table presents the average forecast error for software companies when we winsorize outliers by removing forecast errors that exceed the 99th percentile in absolute value for each forecast horizon. We present results across various subperiods. Panel A details results for the entire 28-year span from 1996 to 2023. Panels B and C focus on the intervals 1996-2005, 2006-2023, respectively. We include t-statistics in square brackets, calculated using standard errors that are clustered by both firm and year-quarter. All forecast errors are presented as percentages.

Table A.8. Biases in Analysts' Forecasts: Robustness to Market Cap

	Ι	II		III	
	Software (1)	All non-software (2)	I - II (3)	Non-software growth (4)	I - III (5)
Forecast horiz	on: 1 quarter				
Average bias	2.25	1.46	0.79	1.80	0.45
$t ext{-}statistic$	[8.99]	[6.81]	[2.96]	[4.72]	[1.15]
Observations	13,143	178,714	191,857	22,861	36,004
Forecast horiz	on: 2 quarter	$\mathbf{S}$			
Average bias	1.66	-0.18	1.84	-0.80	2.46
$t ext{-}statistic$	[2.80]	[-0.38]	[2.91]	[-0.90]	[2.64]
Observations	$12,\!174$	162,505	174,679	20,958	33,132
Forecast horiz	on: 3 quarter	$\mathbf{S}$			
Average bias	1.92	-1.72	3.64	-4.85	6.76
$t ext{-}statistic$	[2.13]	[-2.91]	[3.97]	[-4.05]	[4.85]
Observations	11,018	142,100	153,118	18,456	$29,\!474$
Forecast horiz	on: 4 quarter	$\mathbf{S}$			
Average bias	3.11	-2.05	5.16	-7.86	10.98
t-statistic	[2.63]	[-2.83]	[4.25]	[-4.85]	[5.76]
Observations	10,143	124,764	134,907	16,185	26,328

Notes: This table presents the average forecast error for companies that have more than two analysts following the firm. Columns 1, 2, and 4 present regression results for the equation:  $e_{t+h|t}^{(k)} = a_h + u_{t+h}^{(k)}$ , where  $e_{t+h|t}^{(k)}$  is the forecast error for company k at horizon h,  $a_h$  is the average bias at horizon h, and  $u_{t+h}^{(k)}$  is the error term. The regressions are run separately for the set of software companies, all non-software companies, and non-software growth firms. In columns 3 and 5, we estimate the following regression:  $e_{t+h|t}^{(k)} = a + b \cdot 1_{t,sw}^{(k)} + u_{t+h}^{(k)}$ , where  $1_{t,sw}^{(k)}$  is an indicator variable set to one if company k is classified as a software company in period t, and zero otherwise. The coefficient b represents the difference in average bias between software companies and the comparison group. Column 3 uses all non-software companies as the comparison group, while column 5 uses only non-software growth firms. The t-statistics, calculated using standard errors clustered by both firm and date, are reported in square brackets. The forecast errors are expressed in percent. The sample spans from 1996Q1 to 2023Q3.

Table A.9. Biases in Individual Analysts' Forecasts

Subsample of a	narysts covern	ring software companies Forecast horizon in quarters					
Coef	Variable	1	2	3	4		
a $t$ -statistic	1	1.38 [8.36]	0.39 [0.98]	-0.09 [-0.16]	-0.04 [-0.06]		
b t-statistic Observations	$\mathbb{1}_{t,sw}^{(k)}$	$   \begin{array}{c}     1.32 \\     [7.20] \\     460,393   \end{array} $	$ 2.13 \\ [5.51] \\ 344,219 $	$ 2.88 \\ [4.94] \\ 279,823 $	3.22 [4.52] 231,981		

Notes: This table presents regression results for the equation:  $e_{t+h|t}^{(k,i)} = a + b \cdot \mathbbm{1}_{t,sw}^{(k)} + u_{t+h}^{(k,i)}$ , using only the sample of analysts who issue forecasts for software companies. The variable  $\mathbbm{1}_{t,sw}^{(k)}$  is an indicator variable set to one if company k is classified as a software company in period t and zero otherwise.  $e_{t+h|t}^{(k,i)}$  denotes the forecast error of analyst i for firm k. The t-statistics, based on standard errors clustered by both analyst and year-quarter, are reported in square brackets. The forecast error is expressed in percent, and the sample spans from 1996Q1 to 2023Q3.

Table A.10. Biases in Analysts' Forecasts: Other Industries

A: Prepackaged s	oftware (7372)		Forecast horiz	on in quarters	
Coef	Variable	1	2	3	4
a	1	1.76	0.51	0.70	2.34
t- $statistic$		[2.82]	[0.35]	[0.39]	[1.10]
Observations		5,677	3,958	3,164	$2,\!573$
B: Computer pro	gramming, data p	rocessing (7370	) Forecast horiz	on in quantons	
Coef	Variable	1	2	3	4
a	1	1.53	1.02	0.67	0.62
$t ext{-}statistic$		[4.64]	[1.58]	[0.75]	[0.60]
Observations		$29,\!267$	$22,\!321$	17,970	14,356
C: Semiconductor	rs and related dev	ices (3674)			
			Forecast horiz	on in quarters	
Coef	Variable	1	2	3	4
a	1	1.68	0.64	-0.35	-0.68
$t ext{-}statistic$		[5.09]	[0.62]	[-0.25]	[-0.40]
Observations		19,989	16,183	14,273	12,560
D: Computer inte	egrated systems de	esign (7373)			
			Forecast horiz	on in quarters	
Coef	Variable	1	2	3	4
a	1	1.01	-0.14	-0.55	-0.26
$t ext{-}statistic$		[3.49]	[-0.21]	[-0.51]	[-0.18]
Observations		5,304	[3,797]	3,199	2,784
E: Data processir	ng and preparation	n (7374)			
			Forecast horiz	on in quarters	
Coef	Variable	1	2	3	4
a	1	1.19	1.10	1.27	2.29
$t ext{-}statistic$		[1.69]	[1.26]	[1.16]	[1.71]
Observations		9,523	7,379	6,125	5,163
F: Computer faci	lities management	(3576)			
		· 	Forecast horiz	on in quarters	
Coef	Variable	1	2	3	4
a	1	1.31	1.04	0.82	0.72
$t ext{-}statistic$		[3.98]	[1.47]	[0.74]	[0.49]
Observations		9,633	7,668	6,711	5,975

Notes: This table presents the average forecast error for individual analysts covering non-software companies in industries related to the software sector. We identify these industries by examining the coverage of analysts who issue forecasts for both software and non-software companies. The top 6 industries are selected based on the frequency of such overlapping coverage. Panels A to F report the average forecast errors for non-software companies within the Prepackaged Software industry (SIC code 7372), Computer Programming and Data Processing (7370), Semiconductors and Related Devices (3674), Computer Integrated Systems Design (7373), Data Processing and Preparation (7374), and Computer Facilities Management (3576). For each industry, we provide the corresponding SIC code in parentheses. The t-statistics, calculated using standard errors clustered by both firm and year-quarter, are reported in square brackets. All forecast errors are expressed as percentages.

Table A.11. Learning within a Specific Forecaster

		Forecast horizon in quarters							
Coef	Variable	1	2	3	4				
$\overline{a}$	1	3.05	3.11	3.85	4.06				
$t ext{-}statistic$		[11.96]	[6.12]	[4.57]	[3.82]				
b	$\mathbb{1}_{t,Medium}^{(k,i)}$	-0.40	-0.48	-0.90	-0.40				
$t ext{-}statistic$	,	[-2.07]	[-1.59]	[-1.63]	[-0.63]				
c	$\mathbb{1}_{t,High}^{(k,i)}$	-0.90	-1.63	-2.85	-2.69				
$t ext{-}statistic$	-,	[-3.26]	[-4.02]	[-4.22]	[-3.35]				
Observations		105,641	76,775	62,492	53,162				

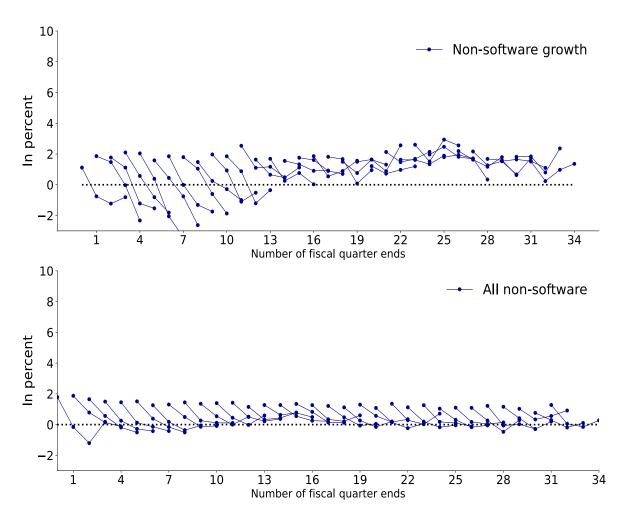
Notes: This table presents regression results for the equation:  $e_{t+h|t}^{(k,i)} = a + b \cdot \mathbb{1}_{t,Medium}^{(k,i)} + c \cdot \mathbb{1}_{t,High}^{(k,i)} + u_{t+h}^{(k,i)}$ , where  $\mathbb{1}_{t,Medium}^{(k,i)}$  and  $\mathbb{1}_{t,High}^{(k,i)}$  are indicator variables taking a value of 1 if analyst i has issued a medium or high number of forecasts, respectively, about software company k. The medium and high thresholds are based on the middle and top terciles of the distribution of the number of forecasts made by all analysts. t-statistics, based on standard errors clustered by both analyst and year-quarter, are reported in square brackets. Forecast errors are expressed in percent, and the sample spans from 1996Q1 to 2023Q3.

Table A.12. Learning within the Consensus Forecast

		Forecast horizon in quarters						
Coef	Variable	1	2	3	4			
$\overline{a}$	1	2.92	3.17	4.42	5.13			
$t ext{-}statistic$		[4.68]	[2.16]	[1.68]	[1.34]			
b	$\mathbb{1}_{t.Medium}^{(k)}$	-0.94	-1.54	-2.42	-1.76			
$t ext{-}statistic$	,	[-1.16]	[-0.93]	[-0.88]	[-0.44]			
c	$\mathbb{1}_{t,High}^{(k)}$	-1.13	-2.49	-3.95	-4.44			
$t ext{-}statistic$	-,-109.0	[-1.64]	[-1.61]	[-1.47]	[-1.15]			
Observations		13,418	12,894	$12,\!244$	11,605			

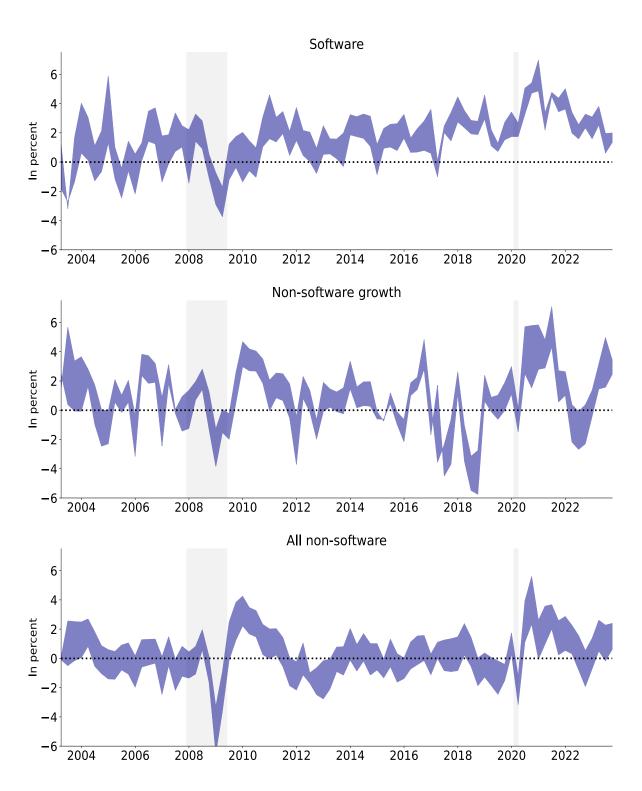
Notes: This table presents regression results for the equation:  $e_{t+h|t}^{(k)} = a + b \cdot \mathbb{1}_{t,Medium}^{(k)} + c \cdot \mathbb{1}_{t,High}^{(k)} + u_{t+h}^{(k)}$ , where  $\mathbb{1}_{t,Medium}^{(k)}$  and  $\mathbb{1}_{t,High}^{(k)}$  are indicator variables taking a value of 1 if the analysts' consensus has issued a medium or high number of forecasts, respectively, about software company k. The medium and high thresholds are based on the middle and top terciles of the distribution of the number of forecasts made for each company k at each time period t. t-statistics, based on standard errors clustered by both analyst and year-quarter, are reported in square brackets. Forecast errors are expressed in percent, and the sample spans from 1996Q1 to 2023Q3.

Fig. A.3. Learning within a Specific Forecaster



Notes: This figure shows the average forecast error for non-software growth companies (upper panel) and all non-software companies (lower panel) based on the number of prior forecasts an analyst i has issued for company k before time t. Each line represents the average forecast error for the current quarter and the subsequent three quarters. The sample covers the period from 1996 to 2023.

Fig. A.4. Biases in Firm Forecasts



Notes: This figure reports the mean forecast errors associated with one-quarter-ahead management guidance values for software and non-software firms, in percentages. The bands represent the range of forecasts provided by management. The gray shaded bars represent NBER recession dates. The figure spans from 2003 to 2023.

Table A.13. Performance Evaluation and Alphas: Subsample Analysis

A: Equally-weighted returns

 $t ext{-}statistic$ 

[2.28]

	Software	minus all no	n-software	Software ma	inus non-soft	ware growth
	1996 - 2023 (1)	1996 - 2005 (2)	2006 - 2023 (3)	1996 - 2023 (4)	1996 - 2005 (5)	2006 - 2023 (6)
Average return spread	7.61	11.30	5.56	11.48	19.78	6.88
t-statistic	[2.12]	[1.27]	[2.06]	[4.05]	[3.62]	[3.84]
Three-factor alpha	6.16	12.20	4.21	11.30	17.37	7.52
t-statistic	[2.38]	[1.85]	[2.80]	[4.64]	[3.10]	[4.57]
Four-factor alpha	6.12	13.37	4.01	10.59	15.99	7.36
$t ext{-}statistic$	[2.48]	[2.15]	[2.52]	[4.78]	[3.08]	[4.38]
B: Value-weighted retu	rns					
<u> </u>		minus all no	n-software	Software ma	inus non-soft	ware growth
	1996 - 2023	1996 - 2005	2006 - 2023	1996 - 2023	1996 - 2005	2006 - 2023
	(1)	(2)	(3)	(4)	(5)	(6)
Average return spread	5.71	5.57	5.79	4.71	8.17	2.78
t- $statistic$	[2.11]	[0.90]	[2.59]	[2.49]	[1.93]	[1.56]
Three-factor alpha	4.85	12.65	3.99	3.46	10.63	2.40
t- $statistic$	[2.37]	[2.50]	[2.18]	[1.78]	[2.31]	[1.22]
Four-factor alpha	[4.75]	12.59	3.91	[3.35]	10.85	[2.29]

Notes: This table presents performance evaluation measures and factor alphas for long-short portfolios, with Panel A focusing on equally-weighted portfolios and Panel B on value-weighted portfolios. In both panels, Columns 1 to 3 show results for the portfolio that buys software companies and sells all non-software companies, while Columns 4 to 6 present results for the portfolio that buys software companies and sells non-software growth companies. All returns are annualized and expressed as a percentage per year by multiplying monthly returns by 1,200. The t-statistics are reported in brackets. The sample period spans from January 1996 through December 2023.

[2.14]

[2.09]

[1.66]

[1.99]

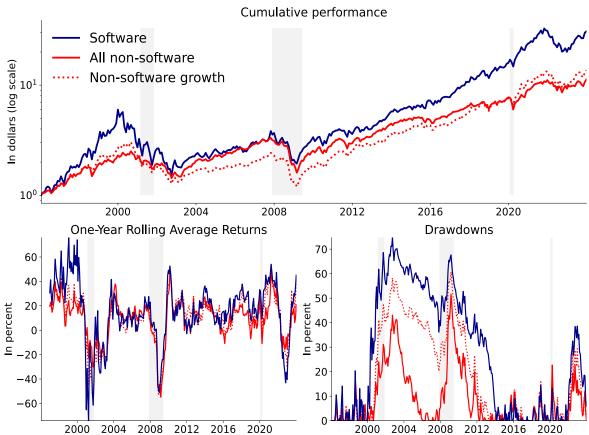
[1.13]

Table A.14. Performance Evaluation and Alphas: Controlling for microcap stocks

A: Equally-weighted re		non-microcap minus all no		Software ma	inus non-soft	ware growth
	1996 - 2023 (1)	1996 - 2005 (2)	2006 - 2023		1996 - 2005 (5)	
Average return spread t-statistic	7.13 [1.87]	7.93 [0.82]	6.68 [2.37]	7.21 [2.66]	11.98 [1.89]	4.57 [2.28]
Three-factor alpha	5.23	10.05	4.77	6.53	10.90	4.67
$t ext{-}statistic$	[0.92]	[1.46]	[3.05]	[2.78]	[1.75]	[2.93]
Four-factor alpha	4.83	10.31	4.45	5.63	8.98	4.44
$t ext{-}statistic$	[2.16]	[1.74]	[2.66]	[3.02]	[1.76]	[2.62]
B: Equally-weighted re	turns using r	nicrocaps				
1 1	_	minus all no	n-software	Software ma	inus non-soft	ware growth
	1996 - 2023 (1)	1996 - 2005 (2)	2006 - 2023	1996 - 2023 (4)	1996 - 2005 (5)	2006 - 2023 (6)
Average return spread	9.05	17.17	4.54	17.78	29.01	11.54
t-statistic	[2.38]	[2.05]	[1.65]	[5.11]	[4.76]	[6.15]
Three-factor alpha	8.40	17.06	4.30	18.37	25.01	12.98
t-statistic	[2.54]	[2.15]	[2.01]	[5.83]	[4.04]	[6.00]
Four-factor alpha	[9.07]	20.74	[4.17]	18.01	25.32	12.81
t-statistic	[2.39]	[2.41]	[1.99]	[5.56]	[3.88]	[6.09]

Notes: This table presents performance evaluation measures and factor alphas for long-short portfolios, with Panel A focusing on equally-weighted portfolios using non-microcap stocks and Panel B on equally-weighted portfolios using microcap stocks. Microcap stocks are those smaller than the 20th percentile of the market equity for NYSE stocks. In both panels, Columns 1 to 3 show results for the portfolio that buys software companies and sells all non-software companies, while Columns 4 to 6 present results for the portfolio that buys software companies and sells non-software growth companies. All returns are annualized and expressed as a percentage per year by multiplying monthly returns by 1,200. The t-statistics are reported in brackets. The sample period spans from January 1996 through December 2023.

Fig. A.5. Cumulative Returns on Value-weighted Portfolios



Notes: The top panel plots the cumulative returns to a value weighted portfolio of software companies, non-software companies, and non-software growth companies from January 1996 to December 2023. The y-axis is on a log scale and all portfolios start with a \$1 investment in 1996, assuming no transaction costs. The lower left panel plots rolling one-year returns for each portfolio, and the lower right panel shows the drawdown of each portfolio, which measures the maximum loss from a peak to a trough before a new peak is attained.

Table A.15. Performance Evaluation and Alphas: Value firms

	Software value minus non-software value					
	1996 - 2023 (1)	1996 - 2005 (2)	2006 - 2023 (3)			
Average return spread	8.01	12.82	5.34			
t-statistic	[1.90]	[1.27]	[1.51]			
Three-factor alpha	7.85	11.98	5.14			
t-statistic	[2.20]	[1.27]	[2.18]			
Four-factor alpha	7.72	11.35	5.23			
t-statistic	[2.76]	[1.42]	[2.28]			

Notes: This table presents performance evaluation measures and factor alphas for long-short value-weighted portfolios. Columns 1 to 3 show results for the portfolio that buys software value companies and sells non-software value companies. We classify a company as value if it belongs to the highest five deciles of portfolios sorted on Book-to-Market ratio. Returns are annualized and expressed in percent per year by multiplying monthly returns by 1,200. The t-statistics are reported in brackets. The sample spans from January 1996 through December 2023.

Table A.16. Performance Evaluation and Alphas: Value-minus-growth returns

		Value minus growth	
-	1996 - 2023	1996 - 2005	2006 - 2023
	(1)	(2)	(3)
Average return spread	2.12	11.56	-3.13
t- $statistic$	[0.39]	[0.91]	[-0.93]
Three-factor alpha	2.54	-0.18	-0.55
t- $statistic$	[0.64]	[-0.02]	[-0.18]
Four-factor alpha	2.15	-2.48	-0.25
t- $statistic$	[0.66]	[-0.26]	[-0.08]
B: Sample of non-software co	ompanies		
		Value minus growth	
-	1996 - 2023	1996 - 2005	2006 - 2023
	(1)	(2)	(3)
Average return spread	-0.70	5.84	-4.33
t-statistic	[-0.23]	[0.99]	[-1.57]
Three-factor alpha	-1.83	-3.24	-2.49
t-statistic	[-1.81]	[-1.99]	[-2.41]
Four-factor alpha	-1.82	-2.92	-2.48

Notes: This table presents performance evaluation measures and factor alphas for value-growth value-weighted portfolios. Panel A reports results for the sample of software companies, while Panel B reports results for the sample of non-software companies. All returns are annualized and expressed as a percentage per year by multiplying monthly returns by 1,200. The t-statistics are reported in brackets. The sample period spans from January 1996 through December 2023.

Table A.17. Coibion-Gorodnichenko Regressions using Long-Term Forecasts

	<u>Software</u> Forecast horizon in years				Non-soft ast horize	ware on in yea	rs		
	1	2	3	4		1	2	3	4
Data consensus t-statistic	0.09 [3.63]	0.16 [2.67]	0.27 [1.34]	_ _		0.05 [4.87]	0.03 [1.05]	0.21 [3.86]	
Data individual $t$ -statistic	$0.15 \\ [5.51]$	0.27 [2.69]	0.55 [1.88]	_		0.05 [2.08]	0.02 [0.57]	0.19 [2.47]	_

Notes: This table presents Coibion-Gorodnichenko regression coefficients for horizons of one, two, and three years. The t-statistics are presented in brackets, where standard errors are clustered by both firm and date. The forecast horizons are in years, and the forecast errors and forecast revisions used in the tests are expressed in percent. The sample spans from 1996 to 2023.

## Appendix B Additional analyses

This section presents additional robustness tests and analyses. The subsections are self-contained, enabling readers to selectively navigate through them without loss.

### B.1 Stock return predictability around revenue announcements

In this section, we examine the predictability of stock returns around revenue announcements. Specifically, we investigate the immediate price reactions in the minutes following quarterly revenue announcements, as well as the long-term price dynamics over the year following the same announcements.

Immediate stock price reaction. We use high-frequency data to show the differential price reaction to revenue announcements for software, all non-software and non-software growth companies in a narrow window around the time of revenue announcement. The high-frequency data comes from the New York Stock Exchange (2003–2023) Trade and Quote (TAQ) dataset, and we consider all stocks traded in the New York Stock Exchange, American Stock Exchange, and Nasdaq National Market System stock markets.

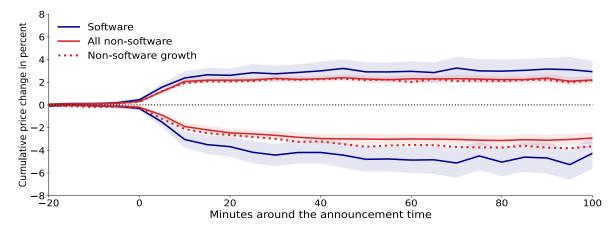
Each quarter, we sort firms into low, medium, and high tercile portfolios based on the news from the quarter-t revenue announcement. Figure B.1 displays the cumulative stock price response in the 20 minutes preceding and the 100 minutes following the revenue announcement for the low and high terciles. While the three sets of firms experience similar price reactions to positive news, software firms exhibit a larger negative price response to negative revenue news, followed by non-software growth and then all non-software companies. Specifically, these companies experience an immediate drop in prices, and the price reaction to bad news continues to trend downward in subsequent minutes, reaching approximately -4.26%, -3.65%, and -2.91% for software, non-software growth, and all non-software companies, respectively, 90 minutes post-announcement.

Long-term stock price dynamics. To explore the long-term price dynamics, we examine the daily returns in the year following the revenue announcement. Since we focus on longer time windows, we control for aggregate market movements by computing Fama-French three-factor adjusted returns (FF3 adjusted returns). For the daily returns we use the CRSP daly stock file (Center for Research in Security Prices, 1996–2023a).

We stratify firm observations into terciles based on the time-t revenue surprises and calculate mean FF3-adjusted realized returns for a total of four quarters following the time-t revenue announcement, where quarter 0 is defined as the quarter immediately following the announcement. Moreover, each quarter is defined as starting on the day of the t + h revenue announcement and ending one day before the following revenue announcement date.

Panel A of Table B.1 presents the results, with standard errors clustered at both the firm and year-quarter levels. We first focus on the price reaction following low revenue surprises. Consistent with the high-frequency results in Figure B.1, we observe that in the quarter of the revenue announcement (i.e., quarter 0), the average quarterly abnormal return for software firms reporting low revenue surprises is -3.81% (column 1), while the corresponding returns for non-software firms and non-software growth firms are -2.83% (column 3) and -2.70% (column 5), respectively. However, over the four quarters following the announcement, the quarterly negative abnormal returns for software firms

Fig. B.1. High-Frequency Stock Price Reaction to Revenue Announcements



Notes: This figure shows the differential price reaction to revenue announcements for software (darkblue), non-software growth (dotted red line), and all non-software firms (red), in percentages. We sort firms into terciles based on revenue announcement news in quarter t. We show the average percent change in price in the 20 minutes before and the 100 minutes following firm revenue announcements with 99% confidence intervals. We obtain NYSE Trade and Quote (TAQ) intraday transaction data for all firms listed on the New York Stock Exchange, American Stock Exchange, and Nasdaq National Market System stock markets and measure the percent change in price over the noted window of time for the period spanning April 2003 through December 2022.

become positive and statistically significant, with mean quarterly abnormal returns of 1.84% (t-statistic = 2.03), 2.08% (t-statistic = 2.50), 1.28% (t-statistic = 1.54), and 2.46% (t-statistic = 2.60), respectively. In contrast, the mean quarterly abnormal returns for non-software firms and non-software growth firms are close to zero and statistically insignificant.

Columns 2, 4, and 6 of Panel A in Table B.1 present the results on the price reaction following high revenue surprises. Column 2 displays the quarterly mean abnormal returns for software companies with the highest revenue surprises. The mean abnormal return is positive and high for the first quarter, with a value of 4.27% (t-statistic = 6.53). In the subsequent four quarters, the average quarterly abnormal returns for software firms remain positive, with values ranging between 0.36% and 0.71%. On the other hand, columns 4 and 6 show that mean abnormal returns for non-software and non-software growth companies are positive only in the first quarter, with a value of about 2.5%, and close to zero and statistically insignificant for the subsequent quarters. Panel B of Table B.1 shows robustness results using Fama–French/Carhart's four-factor model-adjusted returns.

Table B.1. Quarterly Abnormal Returns around Revenue Announcements

A: Average three	A: Average three-factor adjusted returns									
	Softv	vare	A	All non-software			Non-software growth			
Quarter after announcement	Low (1)	High (2)	-	Low (3)	High (4)		Low (5)	High (6)		
0 quarter  t-statistic 1 quarter  t-statistic 2 quarter  t-statistic 3 quarter	-3.81 [-4.23] 1.84 [2.03] 2.08 [2.50] 1.28	4.27 [6.53] 0.49 [0.91] 0.71 [1.32] 0.42	[- - [- -	2.83 5.93] 0.18 0.32] 0.09 0.17] 0.08	2.48 [6.78] -0.04 [-0.14] 0.00 [0.01] -0.15		-2.70 [-5.33] -0.11 [-0.19] 0.00 [0.00] -0.03	2.48 [6.39] -0.04 [-0.12] 0.06 [0.24] -0.08		
t-statistic 4 quarter t-statistic	[1.54] 2.46 [2.60]	[0.72] $0.36$ $[0.75]$		0.24] $0.25$ $0.52]$	[-0.58] -0.17 [-0.75]		[-0.08] 0.31 [0.63]	[-0.27] -0.12 [-0.52]		

B: Average four-factor adjusted returns

3	Software		All non-	-software	Non-softv	Non-software growth	
Quarter after announcement	$ \begin{array}{c} \text{Low} \\ (1) \end{array} $	High (2)	$ \begin{array}{c} \text{Low} \\ (3) \end{array} $	High (4)	$ \begin{array}{c} \text{Low} \\ (5) \end{array} $	High (6)	
0 quarter  t-statistic 1 quarter  t-statistic	-3.93 [-4.82] 1.62 [2.16]	4.09 [6.59] 0.31 [0.57]	-3.03 [-9.52] -0.43 [-1.31]	2.34 [7.87] -0.14 [-0.52]	-2.91 [-8.81] -0.37 [-1.09]	2.35 [7.71] -0.11 [-0.39]	
2 quarter  t-statistic 3 quarter  t-statistic	1.75 [2.27] 1.10 [1.44]	0.62 [1.14] 0.22 [0.37]	-0.31 [-0.96] -0.19 [-0.78]	-0.09 [-0.40] -0.27 [-1.29]	-0.25 [-0.72] -0.15 [-0.61]	-0.01 [-0.05] -0.20 [-0.86]	
4  quarter t-statistic	2.23 [2.53]	$0.25 \\ [0.54]$	$0.07 \\ [0.22]$	-0.30 [-1.65]	0.12 [0.37]	-0.25 [-1.39]	

Notes: This table presents realized quarterly abnormal returns for portfolios sorted based on revenue news for quarters h=0,1,2,3,4, where quarter 0 is the quarter immediately following the revenue announcement. Firms are sorted into terciles based on revenue announcement news in quarter 0. Panel A reports results using the Fama-French three-factor (FF3) model, while Panel B shows robustness results using the Fama-French/Carhart four-factor (FF4) model. To compute abnormal returns, we use the FF3 or FF4 model with a rolling 252-daily estimation window (requiring a minimum of 126 days of data) to estimate factor betas. The realized return for each quarter is measured starting on the day of the t+h revenue announcement and ending one day before the following revenue announcement date. The sample period spans from December 1996 through December 2023.

Panel A of Table B.2 presents the cumulative FF3 abnormal returns over the first four quarters following a revenue surprise. Column 1 shows that for software firms in the lowest tercile, initially negative returns are observed. However, returns reverse by the third quarter, resulting in a cumulative positive return. In contrast, non-software and non-software growth firms exhibit a much flatter price response in the quarters following the revenue announcement, with no evidence of reversals. Panel B of Table B.2 reports

Table B.2. Cumulative Abnormal Returns around Revenue Announcements

Panel A: Cumulative three-factor adjusted returns								
	Software		All non-	All non-software		Non-software growth		
Cumulative period	Low (1)	High (2)	$ \begin{array}{c} \text{Low} \\ (3) \end{array} $	High (4)	Low (5)	High (6)		
0 quarter to 0 quarter t-statistic	-3.81 [-4.23]	4.27 [6.53]	-2.83 [-5.93]	2.48 [6.78]	-2.70 [-5.33]	2.48 [6.39]		
0 quarter to 1 quarter $t$ -statistic	-2.46 [-1.51]	4.96 [4.98]	-2.73 [-3.08]	$\begin{bmatrix} 2.50 \\ [5.78] \end{bmatrix}$	-2.49 [-2.66]	$\begin{bmatrix} 2.52 \\ [5.57] \end{bmatrix}$		
0 quarter to 2 quarter $t$ -statistic	-0.15 [-0.05]	5.64 [4.34]	-3.28 [-3.89]	2.68 [4.88]	-3.06 [-3.47]	2.77 [4.89]		
0 quarter to 3 quarter $t$ -statistic	1.90 [0.44]	5.99 [3.66]	-3.16 [-3.33]	2.76 [4.47]	-2.88 [-2.93]	2.88 [4.50]		
0 quarter to 4 quarter $t$ -statistic	5.84 [0.95]	5.84 [3.11]	-2.74 [-2.57]	2.67 [3.88]	-2.38 [-2.15]	$\begin{bmatrix} 2.85 \\ [4.05] \end{bmatrix}$		

Panel B: Cumulative four-factor adjusted returns

	Software		All non-	software	Non-software growth		
Cumulative period	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)	
0 quarter to 0 quarter $t$ -statistic	-3.93 [-4.82]	4.09 [6.59]	-3.03 [-9.52]	2.34 [7.87]	-2.91 [-8.81]	2.35 [7.71]	
0 quarter to 1 quarter  t-statistic	-2.72 [-1.88]	4.72 [4.83]	-3.30 [-7.11]	2.34 [6.05]	-3.11 [-6.37]	2.39 [6.05]	
0 quarter to 2 quarter  t-statistic 0 quarter to 3 quarter	-0.56 [-0.22] 1.28	5.29 [4.13] 5.40	-3.74 [-7.10] -3.66	2.44 [4.92] 2.40	-3.56 [-6.50] -3.44	2.59 $[5.13]$ $2.58$	
t-statistic 0 quarter to 4 quarter	[0.33] 4.93	[3.37] 5.22	-5.00 [-5.80] -3.28	[4.25] $[2.21]$	[-5.26] -3.00	[4.46] 2.44	
t-statistic	[0.91]	[2.86]	[-4.37]	[3.44]	[-3.83]	[3.75]	

Notes: This table presents cumulative quarterly abnormal returns for portfolios sorted based on revenue news for quarters h=0,1,2,3,4, where quarter 0 is the quarter immediately following the revenue announcement. Firms are sorted into terciles based on revenue announcement news in quarter 0. Panel A reports results using the Fama-French three-factor (FF3) model, while Panel B shows robustness results using the Fama-French/Carhart four-factor (FF4) model. To compute cumulative abnormal returns, we use the FF3 or FF4 model with a rolling 252-daily estimation window (requiring a minimum of 126 days of data) to estimate factor betas. The cumulative return for each quarter is measured starting on the day of the t+h revenue announcement and ending one day before the following revenue announcement date. The sample period spans from December 1996 through December 2023.

additional robustness results using the FF4 model to adjust returns. The findings are consistent with those obtained using the FF3 model.

The initial price dynamics we document are consistent with the findings in Lakonishok et al. (1994) and Skinner and Sloan (2002), which show that growth firms experience an asymmetrically large negative price reaction to negative surprises. These papers argue that the large price decline reflects overly optimistic expectations, resulting in subsequently

negative returns when those expectations are not met. However, an important difference in our findings is that the initial large negative price reaction for software firms reverses within two quarters, indicating that investors were initially too pessimistic and ended up overreacting to revenue surprises. This result also differentiates our findings from the large literature on post-earnings announcement drift, as the price drift for software firms persists for several quarters.

## B.2 Refining the classification of software companies

In this section, we refine our classification of software companies by expanding our criteria to include all firms that report any source of revenue from software products, rather than relying on a single classification based on the majority of revenue coming from software. We find that the magnitude of both analysts' forecast errors and factor alphas increases monotonically with the percentage of revenue attributed to software.

We utilize the FactSet RBICS with Revenue (2023) dataset to obtain the revenue percentages associated with each standardized reported business segment. From this dataset, we select all firms that create and sell software with varying degrees of software revenue contribution. We then sort these firms into low, medium, and high terciles based on the percentage of total revenue assigned to software by each company. These sorts are formed using the revenue information from each firm's most recent publicly available annual filing and are updated accordingly when a new annual filing becomes available. To avoid any forward-looking bias, we only use unrevised historical data. As this dataset is only available since July 2012, our analysis covers the period from July 2012 to December 2023.

Panel A of Table B.3 reports the analysts' mean forecast errors for firms in each of the low, medium, and high revenue share from software terciles. As a measure of analyst forecast, we use the median analysts' consensus. Companies that do not report revenues from software are labeled as "None" in the table. Across forecasting horizons (reported in each row in the table), we find a monotonic relationship between analysts' forecast errors and the percentage of total revenue assigned to software by each company. For example, at the fourth quarter horizon, firms in the lowest tercile, which derived an average of around 10% of their revenue from software, had a mean forecast error of approximately -0.48%, which is not statistically significant (t-statistic = -0.56). In contrast, firms in the medium and highest tercile, which derived 64% and 100% of their revenue from software products, have an average forecast error of 2.99% (t-statistic = 1.74) and 4.26% (t-statistic = 3.13), respectively. We also report the average forecast error of non-software companies, which is negative and equal to -2.15% (t-statistic = -2.78).

Panel B of Table B.3 reports the average mean returns and factor alphas for each of the software-revenue sorted groups, which are computed using equally-weighted portfolios. To form the portfolios, we update the sorts daily based on the percentage of revenue coming from software, using a one-day gap between the day of the ranking and the start of the holding period. We find a monotonic relationship between the factor alphas and the revenue percentage attributed to software terciles, consistent with results on the analysts' forecast errors. For example, the annualized FF3 alpha for the highest tercile is 5.05% (t-statistic = 3.00), the medium tercile is 0.79% (t-statistic = 0.15), while the

Table B.3. Refining the Classification of Software Companies

A: Analysts' mean forecast errors

Revenue from software (median values)

	The verified from Service (integral variety)						
	0.00% None	10% Low	64% Medium	100% High			
Forecast Horizon	(1)	(2)	(3)	(4)			
1 quarter	1.64	1.31	2.21	2.72			
t- $statistic$	[6.51]	[3.43]	[3.13]	[9.44]			
2 quarter	0.15	0.49	1.64	2.61			
$t ext{-}statistic$	[0.32]	[0.75]	[1.74]	[4.31]			
3 quarter	-1.20	0.03	1.19	3.23			
$t ext{-}statistic$	[-1.93]	[0.04]	[0.89]	[3.40]			
4 quarter	-2.15	-0.48	2.99	4.26			
$t ext{-}statistic$	[-2.78]	[-0.56]	[1.74]	[3.13]			

B: Performance measures and factor alphas

Revenue from software (median values)

			,	,
	0.00%	10%	64%	100%
	None	Low	Medium	$\operatorname{High}$
	(1)	(2)	(3)	(4)
Average return	11.52	10.83	15.00	19.20
Standard deviation	15.21	15.44	22.59	18.13
Three-factor alpha	-1.53	-1.57	0.65	4.85
$t ext{-}statistic$	[-1.87]	[-1.02]	[0.12]	[2.63]
Four-factor alpha	-1.27	-1.34	0.79	5.05
$t ext{-}statistic$	[-1.64]	[-0.95]	[0.15]	[3.00]

Notes: This table presents analysts' forecast errors and stock performance for firms sorted by the percentage of revenue derived from software products. We sort firms that generate revenue from software into low, medium, and high terciles based on the percentage of total revenue assigned to software by each company. Firms that do not report revenues from software are labeled as "None". Panel A reports the analysts' forecast errors for each of these groups, where forecast errors are computed as the difference between actual revenue and the median analyst consensus forecast, scaled by the actual revenue in the previous period. Panel B reports performance evaluation measures, including mean returns, FF3 and FF4 alphas for equally-weighted portfolios formed from each of these groups. Returns and alphas are annualized by multiplying monthly returns by 1,200. The t-statistics are reported in brackets. The sample spans from July 2012 to December 2023.

lowest tercile alpha is -1.34% (t-statistic = -0.95). Finally, the FF3 alpha for non-software companies is -1.27% (t-statistic = -1.64).

#### B.3 Customers of software

In this section, we investigate how market participants value non-software companies that are the primary customers of software firms and thus benefit the most from software usage. We find that these companies also experienced positive forecast errors and alphas, albeit significantly smaller in magnitude compared to those found for software companies.

To identify the primary customers of software companies, we utilize the FactSet Supply Chain Relationships (2023) database. This database employs information from SEC 10-K annual filings, investor presentations, and press releases to establish customer-supplier links between firms. Under rule SFAS 131, the U.S. Securities and Exchange Commission (SEC) requires companies to disclose their customers if their revenue exposure to them is 10% or greater. Consequently, the customers identified in our dataset play a significant role in the supplier firms' revenues. A key advantage of the FactSet dataset is that it not only uncovers the direct relationships that companies report but also the reverse relationships in which they are named in other companies' filings. This feature allows for a more comprehensive analysis of customer-supplier links.

As this dataset is only available since April 2003, we begin our analysis in April 2003 by identifying the key customers of software companies that are also included in the IBES/CRSP/Compustat datasets. To ensure that the software-firm-customer relationships are known to market participants at all times, we only update the supply chain relationships when an annual filing becomes publicly available, and we use historical, unrevised data. We conclude the selection process in December 2023.

Once we identify non-software companies that are customers of software companies, we measure the relevance of a customer-supplier relationship using the percentage of firms' revenues derived from their main customers during a given reporting period. Leveraging this information, we compute a measure of the relative importance of such relationships by dividing non-software companies into above- versus below-median bins based on those reported values. We also report results for non-software companies that do not provide this percentage for completeness.

Panel A of Table B.4 reports the analysts' mean forecast errors for customers of software companies, categorized by the strength of their customer-supplier relationship. Columns 4, 5, and 6 present the results for customers with high, low, and missing values for the relationship strength, respectively. Across forecasting horizons (reported in each row of the table), we find positive forecast errors only for non-software customers with a strong economic link to their software suppliers. For example, at the quarterly horizon, customers with above-median values have forecast errors of 1.38% (t-statistic = 2.21), compared to 0.60% (t-statistic = 1.97) for those with below-median values.

Panel B of Table B.4 presents the mean returns and factor alphas for the same group of companies. The key finding is that the factor alphas are positive and statistically significant only for non-software firms with strong customer links to software companies. For example, column 4 shows that the annualized three-factor alpha for customers with above-median values equals 2.27% (t-statistic = 1.90), which is smaller in magnitude than the alpha obtained for software companies (4.32%, t-statistic =2.26, column 1). In contrast, for the other groups of companies, including customers with a relatively weak link (column 5), those with no data on the link (column 6), and companies with no customer relation to software (column 2), the factor alphas are close to zero and not

Table B.4. Supply Chain Relation to Software Firms

#### A: Analysts' mean forecast errors

Supply chain relation to software firms

	Software	No Relevance of the customer rela				he customer relation
Forecast horizon	firms $(1)$	relation (2)	Customers (3)	High (4)	Low (5)	No data (6)
1 Quarter t-statistic	2.47 [11.02]	1.69 [12.05]	1.09 [9.23]	1.38 [2.21]	0.60 [1.97]	1.10 [5.22]
$\begin{array}{c} 2 \; \text{Quarter} \\ \textit{t-statistic} \end{array}$	$2.05 \\ [3.78]$	0.15 [0.63]	0.32 [1.83]	0.84 [1.57]	0.34 [0.64]	0.29 [0.69]
3  Quarter t-statistic	2.63 [3.17]	-1.43 [-3.82]	-0.31 [-1.06]	0.39 [0.51]	-0.53 [-0.68]	-0.34 [-0.56]
$\begin{array}{c} 4 \; \text{Quarter} \\ t\text{-}statistic \end{array}$	3.95 [3.26]	-2.37 [-4.45]	-0.32 [-0.90]	1.02 [1.36]	-1.04 [-1.07]	-0.37 [-0.53]

B: Performance measures and factor alphas

Supply chain relation to software firms

	Software	No		Relevance of the customer relation			
	firms (1)	relation (2)	Customers (3)	High (4)	Low (5)	No data (6)	
Average return	17.42	10.76	13.12	13.89	11.36	13.27	
Standard deviation	21.90	19.34	19.95	17.33	17.59	20.26	
Three-factor alpha	4.32	-1.38	0.13	2.27	-0.54	0.18	
$t ext{-}statistic$	[2.26]	[-0.95]	[0.12]	[1.90]	[-0.40]	[0.14]	
Four-factor alpha $t$ -statistic	4.55 [2.43]	-0.77 [-0.57]	0.70 $[0.72]$	2.71 [2.43]	-0.29 [-0.22]	0.76 [0.72]	

Notes: We rely on the FactSet supply chain relationship database to pinpoint the main customers of software companies. To evaluate the relevance of a customer-supplier relationship, we leverage the percentage of revenue that the software company obtained from this relationship during the reporting period. We then categorize firms into above- versus below-median bins based on the reported values. Panel A reports the mean cumulative forecast error for 4-quarter-ahead analysts' consensus forecasts. Panel B reports annualized alphas. The t-statistics are in brackets. The sample spans from April 2003 to December 2023.

#### statistically significant.

Overall, our analysis reveals significant growth surprises and abnormally high stock returns for firms that are positively impacted by software, which suggest the presence of predictable spillover effects on software companies' principal customers. This result is consistent with previous research (Hong et al., 2007; Cohen and Frazzini, 2008; Menzly and Ozbas, 2010) showing that relevant information affecting firm values diffuses only gradually across economically linked firms, leading to predictable patterns in both quantities, such as revenues, and stock prices.

### B.4 Extending the sample to the 1970s

In our main analysis, we start our sample in 1996 due to the methodology used for classifying companies as software firms, which involves searching each company's annual revenue segment breakdowns in their 10-K filings and identifying those that derive more than 50 percent of their revenues from developing and selling software. However, the SEC only mandated electronic filing of financial reports in the EDGAR repository starting in 1995 or 1996, depending on the firm's size. As a result, accurately classifying software companies using the revenue share approach is only feasible from 1996 onward.

Software, however, existed long before 1996. The adoption of computers began in the 1970s (Greenwood and Jovanovic, 1999), utilizing various programming languages such as Unix, Fortran, COBOL, and FORMAC. In the 1980s, personal computers gained prominence, with Microsoft launching MS-DOS in the early 1980s and the first version of Microsoft Windows in 1985. By the 1990s, software was widespread, although it had not yet achieved the immense scalability it would later experience with the advent of cloud computing.

To extend our analysis back to the 1970s, we employ an alternative classification method based on the Standard Industrial Classification (SIC). Companies self-select their SIC codes based on their primary line of business. We take the SIC code 7372, Prepackaged Software, which is defined as "Establishments primarily engaged in the design, development, and production of prepackaged computer software" as our alternative classification method for software companies. In periods post-1996, where we have access to revenue segment breakdowns, approximately two-thirds of firms with the Prepackaged Software SIC code have more than 50 percent of their revenues coming from software. Moreover, Table B.5 ranks software companies based on the SIC codes and we find that 53.4% of all software companies also have the SIC code 7372 in any given year. This suggests that the broad SIC code 7372 allows us to capture a great share of software companies.

However, it is important to note that SIC code 7372 is not a perfect classification of software companies. Approximately one-third of Prepackaged Software firms are not accurately classified as software firms, as their revenue share from software offerings is below 50%. This is because their revenues include significant hardware, consulting, and/or service revenues which make up the majority of their revenues. Additionally, Table B.5 also shows that 46 percent of firms classified as software firms by FactSet's methodology come from other SIC industries, indicating that using the Prepackaged Software SIC code provides an incomplete classification of software companies. Nonetheless, on the whole, the rough classification still provides valuable insights into the outperformance of software companies in early periods and that this outperformance extends back to the 1970s.

Table B.6 shows the results for the extended 1976 to 2023 sample. Panel A reports mean returns and alphas using equally-weighted portfolios, while Panel B uses value-weighted portfolios. The main takeaway from Table B.6 is that a portfolio of Prepackaged Software companies produces substantial returns and alphas. Columns 3 and 5 show that it outperforms all non-prepackaged software companies and non-prepackaged growth companies, respectively, with factor alphas above 6% and t-statistics above 2.

Table B.7 provides a detailed breakdown of the returns for the prepackaged software

portfolio from 1996 to 2023. Specifically, it categorizes companies with the SIC code 7372 (Prepackaged Software) into two distinct groups based on their revenue sources. The first group consists of prepackaged non-software companies, defined as those with SIC code 7372 but deriving less than 50% of their revenue from software. These companies primarily generate their revenue from hardware, consulting, and/or services. The second group comprises prepackaged (pure-play) software companies, characterized by SIC code 7372 with more than 50% of their revenue coming from software activities.

Table B.7 shows that the superior performance of prepackaged companies is attributable to those firms which derive the majority of their revenue from software offerings. Column 1 presents the returns and alphas for the prepackaged non-software companies. Here, the alpha values for both the value-weighted and equally-weighted returns are statistically insignificant from zero. Additionally, the point estimates for the equally-weighted portfolio (shown in Panel A) are negative. In stark contrast, Column 2 highlights the performance of (pure-play) prepackaged software companies, where the alphas are positive and statistically significant. Column 3 takes a long-short portfolio that is long the portfolio of prepackaged non-software companies and short prepackaged (pure-play) software companies. We document that the mean returns and alphas for this long-short portfolio are negative and statistically significant.

Overall, we find that Prepackaged Software companies have generated abnormally high stock returns relative to standard risk-factor models over the past five decades. Furthermore, we show that the outperformance of these companies, at least for the past two decades, is driven by Prepackaged Software companies that derive 50% or more of their revenue from software offerings.

Table B.5. Proportion of Software Companies by SIC Codes

	Description	Process control instruments						Household audio and video equipment	Employment agencies	Drugs, proprietaries, and sundries	Engineering, Accounting, Research, Management	Telephone communication, except radio	Accounting, auditing, and bookkeeping	Miscellaneous Chemical Products		Electronic computers	,	Nonclassifiable establishments	Investors, nec			•		,		,	_		Diagnostic substances	Fire, marine, and casualty insurance	Analytical instruments		Services, NEC	Electronic Components & Accessories		
	SIC	3823	8742	5961	7323	2836	3825	3651	7361	5122	8700	4813	8721	2890	2834	3571	5531	6666	64.00	6411	4841	2750	3711	3721	7200	7500	7812	7830	2835	6331	3826	8741	8000	3670		
Proportion of software	companies	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.05	0.05	0.05	0.05	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02		
	Rank	37	38	39	40	41	42	43	44	45	46	47	48	49	20	51	52	53	54	55	26	22	228	59	09	61	62	63	64	65	99	29	89	69		
		l software	rogramming, Data Processing	ntegrated systems design	sing and preparation	Patent owners and lessors	Custom computer programming services	Computers, peripherals, and software	Computer Communications Equipment	ripheral equipment, nec	Communication services, nec	ices, nec	Measuring and controlling devices, nec	Semiconductors and related devices	Radio and t.v. communications equipment	Communications equipment, nec	Computer and software stores	Telephone and telegraph apparatus	publishing	ers and dealers	Services	Electronic components, nec	Components, NEC		l physical research	none communication	ines, nec		advice	Personal credit institutions	rvices	Calculating and accounting equipment	Functions related to depository banking	Hobby, toy, and game shops	Medical laboratories	Real estate agents and managers Misc Health & Allied Services, NEC
	Description	Prepackaged software	Computer Programm	Computer integrated	Data processing and	Patent owne	Custom com	Computers, 1	Computer Co	Computer peripheral	Communicat	Business services, nec	Measuring ar	Semiconducto	Radio and t.	Communicati	Computer and	Telephone an	Miscellaneous publish	Security brokers and	Educational Services	Electronic co	Electronic Componen	Special ind	Commercial physical	Radiotelephone comm	Office machines, nec	Advertising	Investment advice	Personal cr	Electric services	Calculatin	Functions	Hobby, to	Medical la	Real estat Misc Heal
	SIC Description	7372 Prepackaged	_	_		_					Ū			3674 Semiconduct							_			_			_	7	_				6099 Functions			6531 Real estat 8090 Misc Heal
Proportion of software	SIC	2	_	2 7373	7374	6794	7371	5045	3576	3577	4899	7389	3829		3663	3669	5734	3661	2741	6211	8200	3679	3679	3559	8731	4812	3579	7310	6282	6141	4911	3578		5945	8071	

Notes: For our sample of software companies from 1996 to 2023, this table reports the percentage of firms belonging to each Standard Industrial Classification (SIC) code in a given year.

Table B.6. Prepackaged Software Performance Evaluation and Alphas Extended Sample: Since the 1970s

A: Equally-weighted	l returns				
	I	II		III	
	Prepackaged software (1)	Non-prepackaged software (2)	I - II (3)	Non-prepackaged growth (4)	I - III (5)
Average return  t-statistic	21.29 [4.99]	13.95 [5.83]	7.33 [2.49]	8.78 [3.11]	12.51 [5.31]
Standard deviation	31.28	18.88	18.81	24.25	14.67
Three-factor alpha $t$ -statistic	6.63 [2.75]	-0.30 [-0.32]	6.92 [3.11]	-5.67 [-4.76]	12.30 [5.75]
Four-factor alpha $t$ -statistic	8.46 [3.27]	1.24 [1.13]	7.22 [3.38]	-3.40 [-2.17]	11.86 [5.72]

B: Value-weighted returns

	I	II		III	
	Prepackaged software (1)	Non-prepackaged software (2)	I - II (3)	Non-prepackaged growth (4)	I - III (5)
Average return	22.25	12.01	10.24	11.27	10.98
$t ext{-}statistic$	[5.26]	[6.24]	[3.05]	[4.63]	[3.46]
Standard deviation	29.43	15.39	21.46	17.59	19.88
Three-factor alpha	9.86	-0.53	10.39	0.07	9.79
$t ext{-}statistic$	[3.44]	[-2.30]	[3.61]	[0.12]	[3.41]
Four-factor alpha	9.89	-0.39	10.28	0.47	9.42
t- $statistic$	[3.71]	[-1.80]	[3.84]	[0.85]	[3.60]

Notes: This table presents performance evaluation measures and factor alphas for prepackaged software companies (SIC code equal to 7372), all non-prepackaged software companies, and non-prepackaged growth companies. In column (3) we form a long-short portfolio that buys the prepackaged software companies and sells all non-prepackaged software companies. In column (5) we form a long-short portfolio that buys the prepackaged software companies and sells non-prepackaged growth companies. Panel A reports results for equally-weighted portfolios, while Panel B reports results for value-weighted returns. We annualize all returns, expressed as a percentage per year, by multiplying monthly returns by 1,200. t-statistics are reported in brackets. The table spans the period from January 1976 through December 2023.

Table B.7. Prepackaged Software vs. Software Companies Performance Evaluation and Alphas

A: Equally-weighted r	I	II	
	Prepackaged	Prepackaged	
	non-software	software	I - II
	(1)	(2)	(3)
Average return	12.89	18.54	-5.64
t- $statistic$	[2.24]	[3.47]	[-2.10]
Standard deviation	32.13	30.90	11.82
Three-factor alpha	-0.66	5.71	-6.37
t- $statistic$	[-0.24]	[1.88]	[-2.35]
Four-factor alpha	1.69	7.26	-5.57
$t ext{-}statistic$	[0.59]	[2.15]	[-2.49]
B: Value-weighted ret	urns		
<u> </u>	I	II	
	Prepackaged	Prepackaged	
	non-software	software	I - II
	(1)	(2)	(3)
Average return	11.66	15.67	-4.01
t- $statistic$	[2.55]	[3.35]	[-1.88]
Standard deviation	22.94	26.04	15.53
Three-factor alpha	0.68	4.27	-3.59
$t ext{-}statistic$	[0.32]	[2.21]	[-1.47]
Four-factor alpha	1.75	4.29	-2.54
t- $statistic$	[0.89]	[2.18]	[-1.06]

Notes: This table presents performance evaluation measures and factor alphas for prepackaged non-software companies and prepackaged software companies. In column (3) we form a long-short portfolio that buys the prepackaged non-software companies and sells all prepackaged software companies. Panel A reports results for equally-weighted portfolios, while Panel B reports results for value-weighted returns. We annualize all returns, expressed as a percentage per year, by multiplying monthly returns by 1,200. t-statistics are reported in brackets. The table spans the period from January 1996 through December 2023.

# Appendix C Learning about software

This section of the Appendix provides supplementary material for the Bayesian learning framework presented in Section 4 of the main text. It consists of the following sections:

C.1 - Data

C.2 - State-Space Representation of the Cash-flow Process

C.3 - Posterior Inference

C.4 - Model-implied Forecasts

C.5 - Solving the Model

C.6 - Supplementary Figures and Tables

C.7 - Alternative Initial Beliefs

### C.1 Data

Section 4 of the main text uses quarterly revenue growth data for software and non-software companies, as well as monthly real per capita consumption growth data.

For the revenue series, we downloaded revenue data (revtq) from WRDS Compustat Quarterly fundamentals for all North American firms. We computed log differences to obtain quarterly growth rates for each firm and then seasonally adjusted the series. To calculate consumption growth rates, we used the seasonally adjusted real personal consumption expenditures on non-durables and services from the Bureau of Economic Analysis (2023) NIPA tables (Table 2.8.3 and Table 2.8.6). We converted this series to per capita terms using mid-quarter population data from NIPA Table 7.1 and then computed growth rates by taking log differences. While the revenue series is at a quarterly frequency, the consumption growth data is at a monthly frequency. Figure C.1 in Section C.6 depicts these series.

# C.2 State-space representation of the cash-flow process

This section presents the state-space representation for the cash-flow process. As described in the main text, we assume that the revenue growth rates and consumption growth follow the specification given below:

$$g_{c,t+1} = \mu_c + x_t + \sigma_{c,t}\eta_{c,t+1}, \quad \eta_{c,t+1} \sim N(0,1),$$

$$x_{t+1} = \rho x_t + \sqrt{1 - \rho^2} \varphi_x \sigma_{c,t}\eta_{x,t+1}, \quad \eta_{x,t+1} \sim N(0,1),$$

$$g_{s,t+1} = \mu_s + \phi_s x_t + \pi_s \sigma_{c,t}\eta_{c,t+1} + \sigma_{s,t}\epsilon_{s,t+1}, \quad \epsilon_{s,t+1} \sim N(0,1),$$

$$g_{ns,t+1} = \mu_{ns} + \phi_{ns} x_t + \pi_{ns}\sigma_{c,t}\eta_{c,t+1} + \sigma_{ns,t}\epsilon_{ns,t+1}, \quad \epsilon_{ns,t+1} \sim N(0,1).$$
(C.1)

The state-space representation consists of a measurement equation and a statetransition equation. The measurement equation is given by:

$$y_{t+1} = A_{t+1} (H_0 + H_1 s_{t+1} + \nu_{t+1})$$
 with  $\nu_{t+1} \sim N(0, R)$ , (C.2)

where  $A_{t+1}$  is a selection matrix that accounts for deterministic changes in  $y_{t+1}$ . This selection matrix is important due to the assumed measurement error model for consump-

tion and the mixed-frequency nature of the growth series. The state vector is denoted by  $s_{t+1}$ .

The state-transition equation is:

$$s_{t+1} = F_0 + F_1 s_t + \nu_{t+1}(h_t)$$
 with  $\nu_{t+1}(h_t) \sim N(0, \Sigma_t)$  (C.3)

where the law of motion for the conditional log volatility processes,  $h_t$  is given by:

$$h_{t+1} = \Psi h_t + w_{t+1} \text{ with } w_{t+1} \sim N(0, \Sigma_h).$$
 (C.4)

The matrices  $H_0$ ,  $H_1$ , R,  $F_0$ ,  $F_1$ ,  $\Sigma_t$ ,  $\Psi$ , and  $\Sigma_h$  depend on the model parameters, with  $\Sigma_t$  also depending on the time t conditional log volatility processes.

First, we describe the measurement equation, followed by a discussion of the statetransition equation and the law of motion for the conditional log volatility processes.

### C.2.1 Measurement equation

The aggregate measurement equation in (C.2) combines the following individual measurement equations:

Measurement equation for consumption growth. As in Schorfheide et al. (2018) we incorporate monthly measurement errors in the consumption process that average out under temporal aggregation. In the main text, we assume these errors average out at the quarterly frequency.

Let the subscript t represent the monthly time as t = 3(j-1) + m, where m indexes the month within quarter j and m = 1, 2, 3. The measurement error model is specified as follows:

$$g_{c,3(j-1)+1}^{o} = g_{c,3(j-1)+1} + \sigma_{\epsilon} \left( \epsilon_{3(j-1)+1} - \epsilon_{3(j-2)+3} \right)$$

$$- \frac{1}{3} \sum_{m=1}^{3} \sigma_{\epsilon} \left( \epsilon_{3(j-1)+m} - \epsilon_{3(j-2)+m} \right) + \sigma_{\epsilon}^{q} \left( \epsilon_{(j)}^{q} - \epsilon_{(j-1)}^{q} \right), \qquad (C.5)$$

$$g_{c,3(j-1)+m}^{o} = g_{c,3(j-1)+m} + \sigma_{\epsilon} \left( \epsilon_{3(j-1)+m} - \epsilon_{3(j-1)+m-1} \right), \quad m = 2, 3.$$

The series  $g_{c,3(j-1)+1}^o$  with the "o" superscript represents the observed consumption growth series, which contains measurement errors. The series  $g_{c,3(j-1)+1}$  without the "o" superscript denotes the true measure of consumption growth. The parameters  $\sigma_{\epsilon}$  and  $\sigma_{\epsilon}^q$  represent the standard deviations of monthly and quarterly consumption measurement errors, respectively.

When aggregating the monthly consumption series to the quarterly frequency using the following equation:

$$g_{c,(j)}^q = c_{(j)}^q - c_{(j-1)}^q = \sum_{\tau=1}^5 \left(\frac{3 - |\tau - 3|}{3}\right) g_{c,3j-\tau+1}.$$
 (C.6)

the monthly measurement errors are averaged out, resulting in

$$g_{c,(j)}^{q,o} = g_{c,(j)}^q + \sigma_{\epsilon}^q \left( \epsilon_{(j)}^q - \epsilon_{(j-1)}^q \right).$$

Measurement equation for revenue growth. We assume that the revenue growth series for software and non-software companies are measured without any measurement errors, denoted as:

$$g_{s,(j)}^{o,q} = g_{s,(j)}^{q}$$

$$g_{ns,(j)}^{o,q} = g_{ns,(j)}^{q}$$
(C.7)

Agents observe these series every quarter j. To link the quarterly series to the monthly frequency of the model, we use the following temporal aggregation function:

$$g_{i,(j)}^{q} = \sum_{\tau=1}^{5} \left( \frac{3 - |\tau - 3|}{3} \right) g_{i,3j-\tau+1} \quad \text{for} \quad i \in \{s, ns\}.$$
 (C.8)

Assuming that t + 1 is the last month of the quarter, we can combine the individual measurement equations together with equation (C.1) and express them in matrix form as follows:

$$y_{t+1} = \begin{bmatrix} g_{c,t+1}^o \\ g_{c,t}^o \\ g_{c,t-1}^o \\ g_{s,t+1}^{q,o} \\ g_{ns,t+1}^{q,o} \end{bmatrix}, \quad A_{t+1} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

In order to obtain an expression for the matrices related to the measurement equation, we first define the vectors of states  $s_{t+1}$ 

$$\begin{split} s_{t+1} = & \left[ x_{t+1}, \ x_t, \ x_{t-1}, \ x_{t-2}, \ x_{t-3}, \ x_{t-4}, \ \sigma_{c,t}\eta_{c,t+1}, \ \sigma_{c,t-1}\eta_{c,t}, \ \sigma_{c,t-2}\eta_{c,t-1}, \ \sigma_{c,t-3}\eta_{c,t-2}, \ \sigma_{c,t-4}\eta_{c,t-3}, \\ & \sigma_{\epsilon}\epsilon_{t+1}, \ \sigma_{\epsilon}\epsilon_{t}, \ \sigma_{\epsilon}\epsilon_{t-1}, \ \sigma_{\epsilon}\epsilon_{t-2}, \ \sigma_{\epsilon}\epsilon_{t-3}, \ \sigma_{\epsilon}\epsilon_{t-4}, \ \sigma_{\epsilon}^{q}\epsilon_{t+1}^{q}, \ \sigma_{\epsilon}^{q}\epsilon_{t+1}^{q}, \ \sigma_{\epsilon}^{q}\epsilon_{t-1}^{q}, \ \sigma_{\epsilon}^{q}\epsilon_{t-2}^{q}, \\ & \sigma_{s,t}\eta_{s,t+1}, \ \sigma_{s,t-1}\eta_{s,t}, \ \sigma_{s,t-2}\eta_{s,t-1}, \ \sigma_{s,t-3}\eta_{s,t-2}, \ \sigma_{s,t-4}\eta_{s,t-3}, \\ & \sigma_{ns,t}\eta_{ns,t+1}, \ \sigma_{ns,t-1}\eta_{ns,t}, \ \sigma_{ns,t-2}\eta_{ns,t-1}, \ \sigma_{ns,t-3}\eta_{ns,t-2}, \ \sigma_{ns,t-4}\eta_{ns,t-3} \right]'. \end{split}$$

Given  $s_{t+1}$ , we write the matrices  $H_0$ ,  $H_1$ , and R as follows:

where we allow for some fixed small measurement errors for revenue growth rates of software and non-software companies.

#### C.2.2 State-transition equations

Next, we derive the coefficients of the state transition equations:

$$s_{t+1} = F_0 + F_1 s_t + \nu_{t+1}(h_t)$$
 with  $\nu_{t+1}(h_t) \sim N(0, \Sigma_t)$   
 $h_{t+1} = \Psi h_t + w_{t+1}$  with  $w_{t+1} \sim N(0, \Sigma_h)$ .

Given  $s_{t+1}$ , we write the matrices  $F_0$ ,  $F_1$ , and  $\Sigma_t$  as follows:  $F_0$  is vector of zeros of size 31.

 $\Sigma_{t}$  is a 31×31 matrix with zeros in every entry expect:  $\Sigma_{t,[1,1]} = (1-\rho^{2})\varphi_{x}^{2}\sigma_{c,t}^{2}; \Sigma_{t,[7,7]} = \sigma_{c,t}^{2}; \Sigma_{t,[12,12]} = \sigma_{\epsilon}^{2}; \Sigma_{t,[18,18]} = (\sigma_{\epsilon}^{q})^{2}; \Sigma_{t,[22,22]} = \sigma_{s,t}^{2}; \Sigma_{t,[27,27]} = \sigma_{ns,t}^{2}.$ 

Finally, the matrices associated with the persistent conditional log volatility processes

 $h_t = [h_{c,t}, h_{s,t}, h_{ns,t}]'$ , can be written as

$$\Psi = \begin{bmatrix} \rho_{h_c} & 0 & 0 \\ 0 & \rho_{h_s} & 0 \\ 0 & 0 & \rho_{h_{ns}} \end{bmatrix}, \quad \Sigma_h = \begin{bmatrix} \sigma_{h_c}^2 (1 - \rho_{h_c}^2) & 0 & 0 \\ 0 & \sigma_{h_s}^2 (1 - \rho_{h_s}^2) & 0 \\ 0 & 0 & \sigma_{h_{ns}}^2 (1 - \rho_{h_{ns}}^2) \end{bmatrix}, \quad \omega_{t+1} = \begin{bmatrix} \omega_{c,t+1} \\ \omega_{s,t+1} \\ \omega_{ns,t+1} \end{bmatrix},$$

with  $\sigma_{i,t} = \varphi_i \sigma \exp(h_{i,t})$  for  $i = \{c, s, ns\}$  and  $\varphi_c = 1$ .

### C.3 Posterior inference

This section provides a detailed description of the Metropolis-within-Gibbs algorithm used to sample from the joint posterior of the model parameters and latent states. We define the following parameter vectors:

$$\Theta_{cf} = \left[ \mu_c, \rho, \varphi_x, \sigma, \sigma_\epsilon, \sigma_\epsilon^q, \mu_s, \phi_s, \pi_s, \varphi_s, \mu_{ns}, \phi_{ns}, \pi_{ns}, \varphi_{ns} \right]', 
\Theta_h = \left[ \rho_{hc}, \sigma_{hc}, \rho_{hs}, \sigma_{hs}, \rho_{hns}, \sigma_{hns} \right]',$$

where  $\Theta_{cf}$  contains the parameters related to the cash-flow process, and  $\Theta_h$  includes the parameters associated with the conditional log volatility processes. Additionally, let  $x_{0:T}$  and  $h_{0:T}$  denote the sequences of latent states and latent volatilities, respectively, from time 0 to T. The complete set of parameters and latent states in the model is represented by  $\Theta = (\Theta_{cf}, \Theta_h, x_{0:T}, h_{0:T})$ .

To perform Bayesian inference about  $\Theta$  and the latent state vector, we first specify a prior distribution  $p(\Theta)$  given by:

$$\mu_{c} \sim N\left(\tilde{\mu}_{c}, \tilde{\sigma}_{\mu_{c}}^{2}\right), \qquad \rho \sim N^{T}\left(\tilde{\rho}, \tilde{\sigma}_{\rho}^{2}\right), \qquad \varphi_{x} \sim N\left(\tilde{\varphi}_{x}, \tilde{\sigma}_{\varphi_{x}}^{2}\right), \qquad \sigma \sim \mathcal{IG}(\tilde{\alpha}_{c}, \tilde{\beta}_{c}),$$

$$\mu_{i} \sim N\left(\tilde{\mu}_{i}, \tilde{\sigma}_{\mu_{i}}^{2}\right), \qquad \phi_{i} \sim N\left(\tilde{\phi}_{i}, \tilde{\sigma}_{\phi_{i}}^{2}\right), \qquad \pi_{i} \sim N\left(\tilde{\pi}_{i}, \tilde{\sigma}_{\pi_{i}}^{2}\right), \qquad \varphi_{i} \sim N\left(\tilde{\varphi}_{i}, \tilde{\sigma}_{\varphi_{i}}^{2}\right),$$

$$\rho_{h_{c}} \sim N^{T}\left(\tilde{\rho}_{h_{c}}, \tilde{\sigma}_{\rho_{h_{c}}}^{2}\right), \qquad \sigma_{h_{c}}^{2} \sim \mathcal{IG}(\tilde{\alpha}_{h_{c}}, \tilde{\beta}_{h_{c}}) \qquad \rho_{h_{i}} \sim N^{T}\left(\tilde{\rho}_{h_{i}}, \tilde{\sigma}_{\rho_{h_{i}}}^{2}\right), \qquad \sigma_{h_{i}}^{2} \sim \mathcal{IG}(\tilde{\alpha}_{h_{i}}, \tilde{\beta}_{h_{i}})$$

$$\sigma_{\epsilon} \sim \mathcal{IG}(\tilde{\alpha}_{\epsilon}, \tilde{\beta}_{\epsilon}), \qquad \sigma_{\epsilon}^{q} \sim \mathcal{IG}(\tilde{\alpha}_{\epsilon_{\sigma}}, \tilde{\beta}_{\epsilon_{\sigma}})$$

for  $i \in \{s, ns\}$  and N,  $N^T$ , and  $\mathcal{IG}$  represent the normal, truncated (outside of the (-1,1) interval) normal, and inverse gamma distributions, respectively. We centered the priors in 1996Q1 around the posterior median estimates of the model using data from 1961Q1 to 1995Q4. Additionally, we set the priors for software parameters equal to the pre-1996 non-software parameter estimates.

After specifying the prior distribution, we update our prior beliefs about the parameter vector  $\Theta$  based on the sample information  $Y^T = \{g_{c,1:T}, g_{s,1:T}^q, g_{ns,1:T}^q\}$ . The updated knowledge regarding  $\Theta$  is summarized by the posterior distribution  $p(\Theta \mid Y)$ , which is linked to the prior distribution through Bayes' theorem:

$$p\left(\Theta \mid Y^{T}\right) = \frac{p\left(Y^{T} \mid \Theta\right)p(\Theta)}{p\left(Y^{T}\right)}.$$

We employ a Metropolis-within-Gibbs algorithm to sample from  $p(\Theta \mid Y^T)$ . We initiate the process with an initial guess of the parameter vector, denoted as  $\Theta^{(0)}$ . Given a draw

 $\Theta^{(k-1)}$ , we generate the next draw  $\Theta^{(k)}$  using the following three steps:

- 1. We draw  $\Theta_{cf}^{(k)}$  conditional on  $\left(Y^T, \Theta_h^{(k-1)}, h_{0:T}^{(k-1)}\right)$  from its posterior distribution using a Metropolis-Hastings step, where we use the Kalman filter to evaluate the likelihood  $p\left(Y^T \mid \Theta_{cf}^{(k)}, h_{0:T}^{(k-1)}\right)$  and to obtain  $x_{0:T}^{(k)}$ .
- 2. We draw the sequence of stochastic volatilities  $h_{0:T-1}^{(k)}$  conditional on  $\left(Y^T, \Theta_{cf}^{(k)}, \Theta_h^{(k-1)}\right)$  using the Kim, Shephard, and Chib (1998) algorithm.
- 3. We use a Gibbs sampling step to draw  $\Theta_h^{(k)}$  conditional on  $\left(Y^T, H_{0:T}^{(k)}, \Theta_{cf}^{(k)}\right)$

This algorithm is iterated to generate 10,000 draws from the posterior distribution of the parameters and states at each time T.

### C.4 Model-implied forecasts

This section aggregates the model-implied forecasts from a monthly to a quarterly frequency. These model-implied quarterly forecasts can then be compared with the quarterly forecasts produced by analysts used in the empirical section of the paper.

To set the notation, let  $Y_{(j)}^{qrt}$  denote the revenue for quarter j which is defined as the sum of monthly revenue over the span of that quarter, that is,

$$Y_{(j)}^{qrt} = Y_{3(j-1)+1}^{mthly} + Y_{3(j-1)+2}^{mthly} + Y_{3(j-1)+3}^{mthly},$$

where  $Y_{3(j-1)+m}^{mthly}$  denotes the revenue for month m within that quarter. Next, log-linearize  $Y_{(j)}^{qrt}$  around a monthly value  $Y_*$ :

$$log(Y_{(j)}^{qrt}) \approx log(3Y_*) + \frac{1}{3Y_*} \left( Y_{3(j-1)+1}^{mthly} - Y_* \right) + \frac{1}{3Y_*} \left( Y_{3(j-1)+2}^{mthly} - Y_* \right) + \frac{1}{3Y_*} \left( Y_{3(j-1)+3}^{mthly} - Y_* \right).$$

Denote with lower cases percentage deviations from the log-linearization point to obtain (i.e.,  $y=\frac{Y}{Y_*}\approx\frac{Y-Y_*}{Y_*})$ 

$$y_{(j)}^{qrt} \approx \frac{1}{3} \left( y_{3(j-1)+1}^{mthly} + y_{3(j-1)+2}^{mthly} + y_{3(j-1)+3}^{mthly} \right),$$

To simplify notation let t + 1 be the first month of quarter j, then it follows that the revenue growth rate from quarter j - 1 to quarter j is equal to the sum of monthly revenue growth rates:

$$g_{y,(j)}^{qrt} = y_{(j)}^{qrt} - y_{(j-1)}^{qrt} = \frac{1}{3} \sum_{m=1}^{3} y_{3(j-1)+m}^{mthly} - \frac{1}{3} \sum_{m=1}^{3} y_{3(j-2)+m}^{mthly}$$

$$= \frac{1}{3} (y_{t+3} + y_{t+2} + y_{t+1}) - \frac{1}{3} (y_t + y_{t-1} + y_{t-2})$$

$$= \frac{1}{3} g_{y,t+3} + \frac{2}{3} g_{y,t+2} + g_{y,t+1} + \frac{2}{3} g_{y,t} + \frac{1}{3} g_{y,t-1}$$

$$A.47$$
(C.9)

where in the last line we define the monthly revenue growth as the log difference in revenue between two consecutive months (i.e.,  $g_{y,t} = y_t - y_{t-1}$ ). We can then take time t conditional expectations to obtain 1-quarter forecasts:

$$\mathbb{E}_{t}g_{y,(j)}^{qrt} = \mathbb{E}_{t}y_{(j)}^{qrt} - y_{(j-1)}^{qrt} = \frac{1}{3}\mathbb{E}_{t}g_{y,t+3} + \frac{2}{3}\mathbb{E}_{t}g_{y,t+2} + \mathbb{E}_{t}g_{y,t+1} + \frac{2}{3}g_{y,t} + \frac{1}{3}g_{y,t-1} \quad (C.10)$$

Equations (C.9) and (C.10) are directly comparable to our empirical analysis, since there we also scaled both actuals and forecasts for quarter j by the actual revenue value realized in quarter j-1. This revenue value is included in the forecasters' information sets when issuing the forecast.

Given (C.9) and (C.10) the 1-quarter forecast error is equal to:

$$g_{y,(j)}^{qrt} - \mathbb{E}_t g_{y,(j)}^{qrt} = \frac{1}{3} \left( g_{y,t+3} - \mathbb{E}_t g_{y,t+3} \right) + \frac{2}{3} \left( g_{y,t+2} - \mathbb{E}_t g_{y,t+2} \right) + \left( g_{y,t+1} - \mathbb{E}_t g_{y,t+1} \right)$$

We can compute in a similar way the model-implied forecast and forecast errors for a 2-quarter forecast horizon. Let t + 1 be the first month of quarter j. Then, the actual 2-quarter growth rate is given by:

$$y_{(j+1)}^{qrt} - y_{(j-1)}^{qrt} = \frac{1}{3} (y_{t+6} + y_{t+5} + y_{t+4}) - \frac{1}{3} (y_t + y_{t-1} + y_{t-2})$$

$$= \frac{1}{3} g_{y,t+6} + \frac{2}{3} g_{y,t+5} + g_{y,t+4} + \dots + g_{y,t+1} + \frac{2}{3} g_{y,t} + \frac{1}{3} g_{y,t-1}$$
(C.11)

Taking time t conditional expectations, we obtain the 2-quarter forecast:

$$\mathbb{E}_{t}y_{(j+1)}^{qrt} - y_{(j-1)}^{qrt} = \frac{1}{3}\mathbb{E}_{t}g_{y,t+6} + \frac{2}{3}\mathbb{E}_{t}g_{y,t+5} + \mathbb{E}_{t}g_{y,t+4} + \dots + \mathbb{E}_{t}g_{y,t+1} + \frac{2}{3}g_{y,t} + \frac{1}{3}g_{y,t-1}$$
(C.12)

Finally, using equations (C.11) and (C.12), we can compute the 2-quarter horizon forecast error:

$$y_{(j+1)}^{qrt} - \mathbb{E}_t y_{(j+1)}^{qrt} = \frac{1}{3} (g_{y,t+6} - \mathbb{E}_t g_{y,t+6}) + \frac{2}{3} (g_{y,t+5} - \mathbb{E}_t g_{y,t+5}) + (g_{y,t+4} - \mathbb{E}_t g_{y,t+4}) + \dots + (g_{y,t+1} - \mathbb{E}_t g_{y,t+1})$$
(C.13)

Next, we compute the model-implied forecast and forecast errors for a 3-quarter forecast horizon. Let t + 1 be the first month of quarter j. Then, the actual 3-quarter growth rate is given by:

$$y_{(j+2)}^{qrt} - y_{(j-1)}^{qrt} = \frac{1}{3} (y_{t+9} + y_{t+8} + y_{t+7}) - \frac{1}{3} (y_t + y_{t-1} + y_{t-2})$$

$$= \frac{1}{3} g_{y,t+9} + \frac{2}{3} g_{y,t+8} + g_{y,t+7} + \dots + g_{y,t+1} + \frac{2}{3} g_{y,t} + \frac{1}{3} g_{y,t-1}.$$
(C.14)

Taking time t conditional expectations, we obtain the 3-quarter forecast:

$$\mathbb{E}_{t}y_{(j+2)}^{qrt} - y_{(j-1)}^{qrt} = \frac{1}{3}\mathbb{E}_{t}g_{y,t+9} + \frac{2}{3}\mathbb{E}_{t}g_{y,t+8} + \mathbb{E}_{t}g_{y,t+7} + \dots + \mathbb{E}_{t}g_{y,t+1} + \frac{2}{3}g_{y,t} + \frac{1}{3}g_{y,t-1}.$$
(C.15)

Finally, using equations (C.14) and (C.15), we can compute the 3-quarter horizon forecast

error:

$$y_{(j+2)}^{qrt} - \mathbb{E}_t y_{(j+2)}^{qrt} = \frac{1}{3} (g_{y,t+9} - \mathbb{E}_t g_{y,t+9}) + \frac{2}{3} (g_{y,t+8} - \mathbb{E}_t g_{y,t+8}) + (g_{y,t+7} - \mathbb{E}_t g_{y,t+7}) + \dots + (g_{y,t+1} - \mathbb{E}_t g_{y,t+1}).$$
(C.16)

Finally, the actual 4-quarter growth rate is given by:

$$y_{(j+3)}^{qrt} - y_{(j-1)}^{qrt} = \frac{1}{3} (y_{t+12} + y_{t+11} + y_{t+10}) - \frac{1}{3} (y_t + y_{t-1} + y_{t-2})$$

$$= \frac{1}{3} g_{y,t+12} + \frac{2}{3} g_{y,t+11} + g_{y,t+10} + \dots + g_{y,t+1} + \frac{2}{3} g_{y,t} + \frac{1}{3} g_{y,t-1}.$$
(C.17)

Taking time t conditional expectations, we obtain the 3-quarter forecast:

$$\mathbb{E}_{t}y_{(j+3)}^{qrt} - y_{(j-1)}^{qrt} = \frac{1}{3}\mathbb{E}_{t}g_{y,t+12} + \frac{2}{3}\mathbb{E}_{t}g_{y,t+11} + \mathbb{E}_{t}g_{y,t+10} + \dots + \mathbb{E}_{t}g_{y,t+1} + \frac{2}{3}g_{y,t} + \frac{1}{3}g_{y,t-1}.$$
(C.18)

Finally, using equations (C.17) and (C.18), we can compute the 4-quarter horizon forecast error:

$$y_{(j+3)}^{qrt} - \mathbb{E}_t y_{(j+3)}^{qrt} = \frac{1}{3} \left( g_{y,t+12} - \mathbb{E}_t g_{y,t+12} \right) + \frac{2}{3} \left( g_{y,t+11} - \mathbb{E}_t g_{y,t+11} \right) + \left( g_{y,t+10} - \mathbb{E}_t g_{y,t+10} \right) + \dots + \left( g_{y,t+1} - \mathbb{E}_t g_{y,t+1} \right).$$
(C.19)

We can derive analytic expressions for these equations using the assumed processes for growth rates from equation (2) in the main text and by computing conditional expectations.

## C.5 Solving the model

This section provides a solution of the model. The endowment process is given by:

$$g_{c,t+1} = \mu_c + x_t + \sigma_{c,t}\eta_{c,t+1}, \quad \eta_{c,t+1} \sim N(0,1),$$

$$x_{t+1} = \rho x_t + \sqrt{1 - \rho^2} \varphi_x \sigma_{c,t}\eta_{x,t+1}, \quad \eta_{x,t+1} \sim N(0,1),$$

$$g_{s,t+1} = \mu_s + \phi_s x_t + \pi_s \sigma_{c,t}\eta_{c,t+1} + \sigma_{s,t}\epsilon_{s,t+1}, \quad \epsilon_{s,t+1} \sim N(0,1),$$

$$g_{ns,t+1} = \mu_{ns} + \phi_{ns}x_t + \pi_{ns}\sigma_{c,t}\eta_{c,t+1} + \sigma_{ns,t}\epsilon_{ns,t+1}, \quad \epsilon_{ns,t+1} \sim N(0,1),$$

$$\sigma_{i,t+1}^2 = (\varphi_i \sigma)^2 + \nu_i \left(\sigma_{i,t}^2 - (\varphi_i \sigma)^2\right) + \sigma_{\omega_i}\omega_{i,t+1}, \quad \omega_{i,t+1} \sim N(0,1), \quad \text{for} \quad i \in \{c, s, ns\},$$

where the last equation uses the Schorfheide et al. (2018) linear approximation of the volatility process around the unconditional mean of h, with  $\sigma_{\omega_i} = 2(\varphi_i \sigma)^2 \sigma_{h_i}$  and  $\nu_i = \rho_{h_i}$ .

Given the Epstein-Zin preference for the representative agent, the logarithm of the real stochastic discount factor (SDF) is given by:

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi} g_{c,t+1} + (\theta - 1) r_{c,t+1}$$
 (C.20)

with  $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$  and  $r_{c,t+1}$  denotes the log return on the consumption claim, which using

the approximation of Campbell and Shiller (1988) is given by:

$$r_{c,t+1} = \kappa_0 + \kappa_1 p c_{t+1} - p c_t + g_{c,t+1}. \tag{C.21}$$

The variable  $pc_{t+1}$  represents the log price-to-consumption ratio, and  $\kappa_0$  and  $\kappa_1$  are constants that depend on the unconditional mean of the price-consumption ratio,  $\bar{p}c$ :

$$\kappa_1 = \frac{\exp(\bar{pc})}{1 + \exp(\bar{pc})}$$
 and  $\kappa_0 = \log(1 + \exp(\bar{pc})) - \kappa_1 \bar{pc}$ .

The Euler equation is:

$$\mathbb{E}_t \left[ \exp \left( m_{t+1} + r_{t+1} \right) \right] = 1, \tag{C.22}$$

We employ this equation to price the consumption claim in Section C.5.1 and to price the cash-flow claims for software and non-software companies in Section C.5.4.

#### C.5.1 Consumption claim

We conjecture that the price-consumption ratio is linear in the state variables:

$$pc_t = A_0 + A_1 x_t + A_2 \sigma_{ct}^2 (C.23)$$

To determine the coefficients As, we substitute the log-linear approximation for  $r_{c,t+1}$  from equation (C.21) and the SDF from equation (C.20) into the Euler Equation given in (C.22). Then, by applying the method of undetermined coefficients, we obtain:

$$A_{1} = \frac{1 - \frac{1}{\psi}}{1 - \kappa_{1}\rho},$$

$$A_{2} = \frac{\theta}{2(1 - \kappa_{1}\nu_{c})} \left[ \left( 1 - \frac{1}{\psi} \right)^{2} + \left( \kappa_{1}A_{1}(\sqrt{1 - \rho^{2}}\varphi_{x})^{2} \right],$$

$$A_{0} = \frac{1}{1 - \kappa_{1}} \left[ \log \delta + \kappa_{0} + \mu_{c} \left( 1 - \frac{1}{\psi} \right) + \kappa_{1}A_{2} \left( 1 - \nu_{c} \right) (\varphi_{c}\sigma)^{2} + \frac{\theta}{2} \left( \kappa_{1}A_{2} \right)^{2} \sigma_{\omega_{c}}^{2} \right].$$
(C.24)

To finalize the derivation of the price-consumption ratio, we must determine the steady-state value of  $pc_t$ . This requires solving the following system of equations:

$$\bar{p}c = A_0 (\bar{p}c) + A_2 (\bar{p}c) (\varphi_c \sigma)^2,$$

$$\kappa_1 = \frac{\exp(\bar{p}c)}{1 + \exp(\bar{p}c)},$$

$$\kappa_0 = \log(1 + \exp(\bar{p}c)) - \kappa_1 \bar{p}c.$$

This system of equations can be solved numerically to find the value of  $\bar{pc}$ .

We next proceed to derive an expression for the real and nominal SDF that will be used when pricing the software and non-software cash-flow streams.

#### C.5.2 Real and nominal SDF

By substituting equation (C.21) and equation (C.23) into (C.20), we can express the real stochastic discount factor (SDF) in terms of the state variables and the underlying shocks:

$$m_{t+1} = (\theta - 1) \left[ \kappa_0 + A_0 \left( \kappa_1 - 1 \right) + \kappa_1 A_2 \left( 1 - \nu_c \right) \left( \varphi_c \sigma \right)^2 \right] - \gamma \mu_c + \theta \log \delta$$

$$- \frac{1}{\psi} x_t + (\theta - 1) A_2 \left( \kappa_1 \nu_c - 1 \right) \sigma_{c,t}^2$$

$$- \gamma \sigma_{c,t} \eta_{c,t+1} - (1 - \theta) \kappa_1 A_1 \sqrt{1 - \rho^2} \varphi_x \sigma_{c,t} \eta_{x,t+1} - (1 - \theta) \kappa_1 A_2 \sigma_{w_c} w_{c,t+1}.$$
(C.25)

Shocks to the real SDF can be written as:

$$m_{t+1} - \mathbb{E}_t [m_{t+1}] = -\lambda_c \sigma_{c,t} \eta_{c,t+1} - \lambda_x \sigma_{x,t} \eta_{x,t+1} - \lambda_{w_c} \sigma_{w_c} w_{c,t+1}$$
 (C.26)

where the  $\lambda$ 's denote the market prices of risk:

$$\lambda_c = \gamma, \qquad \lambda_x = (1 - \theta)\kappa_1 A_1 \sqrt{1 - \rho^2} \varphi_x, \qquad \lambda_{w_c} = (1 - \theta)\kappa_1 A_2.$$

We use the nominal discount factor to price nominal payoffs. It can be obtained by subtracting the inflation rate,  $\pi_{t+1}$ , from the real discount factor,  $m_{t+1}$ :

$$m_{t+1}^{\$} = m_{t+1} - \pi_{t+1}, \tag{C.27}$$

where we use the the dollar sign superscript, "\$", to distinguish nominal from real values. For simplicity, and because it is not relevant for the results, we assume that the inflation rate is constant, i.e.,  $\pi_{t+1} = \bar{\pi}$ .

We will now derive an expression for the one-period risk-free rate, which will be useful when computing realized mean excess returns for software and non-software companies.

#### C.5.3 Risk-free rate

The risk-free rate is affine in the state variables and given by:

$$r_{f,t} = -\mathbb{E}_{t} (m_{t+1}) - \frac{1}{2} \operatorname{Var}_{t} (m_{t+1})$$

$$= -\theta \log \delta + \gamma \mu_{c} + (1 - \theta) \left[ \kappa_{0} + A_{0} (\kappa_{1} - 1) + \kappa_{1} A_{2} (1 - \nu_{c}) (\varphi_{c} \sigma)^{2} \right] - \frac{1}{2} ((1 - \theta) \kappa_{1} A_{2})^{2} \sigma_{w_{c}}^{2}$$

$$+ \frac{1}{\psi} x_{t} + \left( (1 - \theta) A_{2} (\kappa_{1} \nu_{c} - 1) - \frac{1}{2} \gamma^{2} - \frac{1}{2} \left( (1 - \theta) \kappa_{1} A_{1} \sqrt{1 - \rho^{2}} \varphi_{x} \right)^{2} \right) \sigma_{c,t}^{2}.$$
(C.28)

#### C.5.4 Software and non-software cash-flow claims

We now present asset-pricing solutions for the claim on software cash-flows. The solutions for non-software companies can be derived similarly by substituting the s subscript with the ns subscript.

First, we log-linearize the return on software. Let  $D_{s,t+1}$  be the aggregate dividends paid by software companies and  $P_{s,t+1}$  be the stock price. The return on software is given by:

$$R_{s,t+1} = \frac{P_{s,t+1} + D_{s,t+1}}{P_{s,t}} = \frac{1 + \frac{P_{s,t+1}}{D_{s,t+1}}}{\frac{P_{s,t}}{D_{s,t}}} \frac{D_{s,t+1}}{D_{s,t}}.$$
 (C.29)

Assuming the relation between dividends and revenue is  $D_{s,t+1} = Y_{s,t+1}^{\lambda}$ , where  $\lambda$  denotes the elasticity of dividends to changes in revenues (i.e.,  $\frac{\%\Delta D}{\%\Delta Y}$ ), we log-linearize this equation around  $p\bar{d}_s$ , yielding:

$$r_{s,t+1} = \kappa_{0,s} + \kappa_{1,s} p d_{s,t+1} - p d_{s,t} + \lambda g_{s,t+1}, \tag{C.30}$$

where the log-linearization parameters are given by

$$\kappa_{1,s} = \frac{\exp(\bar{p}d_s)}{1 + \exp(\bar{p}d_s)} \quad \text{and} \quad \kappa_{0,s} = \log(1 + \exp(\bar{p}d_s)) - \kappa_{1,s}\bar{p}d_s.$$

The Euler equation that prices the nominal software return  $r_{s,t+1}$  is:

$$\mathbb{E}_{t} \left[ \exp \left( m_{t+1}^{\$} + r_{s,t+1} \right) \right] = 1. \tag{C.31}$$

To solve this equation, we conjecture that the price-dividend ratio takes the form:

$$pd_{s,t} = A_{0,s} + A_{1,s}x_t + A_{2,s,c}\sigma_{c,t}^2 + A_{2,s,s}\sigma_{s,t}^2.$$
 (C.32)

Substituting the log-linear approximation for  $r_{s,t+1}$  from equation (C.30) and the nominal SDF from equation (C.27) into (C.31), we obtain the solutions for the coefficients  $A_{0,s}$ ,  $A_{1,s}$ , and  $A_{2,s}$ :

$$A_{1,s} = \frac{\lambda \phi_{s} - \frac{1}{\psi}}{1 - \kappa_{1,s}\rho},$$

$$A_{2,s,c} = \frac{1}{1 - \kappa_{1,s}\nu_{c}} \left[ (\theta - 1)A_{2} (\kappa_{1}\nu_{c} - 1) + \frac{1}{2} (\lambda \pi_{s} - \gamma)^{2} + \frac{1}{2} (\kappa_{1,s}A_{1,s} + (\theta - 1)\kappa_{1}A_{1})^{2} (1 - \rho^{2})\varphi_{x}^{2} \right]$$

$$A_{2,s,s} = \frac{\frac{1}{2}\lambda^{2}}{1 - \kappa_{1,s}\nu_{s}},$$

$$A_{0,s} = \frac{1}{1 - \kappa_{1,s}} \left[ \theta \log \delta - \gamma \mu_{c} + \kappa_{0,s} + \lambda \mu_{s} - \bar{\pi} + (\theta - 1) (\kappa_{0} + A_{0} (\kappa_{1} - 1) + \kappa_{1}A_{2} (1 - \nu_{c}) (\varphi_{c}\sigma)^{2}) + \kappa_{1,s}A_{2,s,c} (1 - \nu_{c}) (\varphi_{c}\sigma)^{2} + \kappa_{1,s}A_{2,s,s} (1 - \nu_{s}) (\varphi_{s}\sigma)^{2} + \frac{1}{2} (\kappa_{1,s}A_{2,s,s})^{2} \sigma_{\omega_{s}}^{2} + \frac{1}{2} (\kappa_{1,s}A_{2,s,c}(\theta - 1) + \kappa_{1}A_{2})^{2} \sigma_{\omega_{c}}^{2} \right]$$
(C.33)

Similarly, to determine the coefficients  $\kappa_{1,s}$  and  $\kappa_{0,s}$  we solved numerically for  $pd_s$  from

the following system of equations:

$$\bar{p}d_s = A_{0,s} \left(\bar{p}d_s\right) + A_{2,s,c} \left(\bar{p}d_s\right) (\varphi_c \sigma)^2 + A_{2,s,s} \left(\bar{p}d_s\right) (\varphi_s \sigma)^2,$$

$$\kappa_{1,s} = \frac{\exp(\bar{p}d_s)}{1 + \exp(\bar{p}d_s)},$$

$$\kappa_{0,s} = \log(1 + \exp(\bar{p}d_s)) - \kappa_{1,s}\bar{p}d_s.$$

Next, we rewrite the software-return from equation (C.30) as follows:

$$r_{s,t+1} - \mathbb{E}_t \left[ r_{s,t+1} \right] = \beta_{s,c} \sigma_{c,t} \eta_{c,t+1} + \beta_{s,x} \sigma_{c,t} \eta_{x,t+1} + \beta_{s,s} \sigma_{s,t} \epsilon_{s,t+1} + \beta_{s,\omega_c} \sigma_{\omega_c} \omega_{c,t+1} + \beta_{s,\omega_s} \sigma_{\omega_s} \omega_{s,t+1}$$
(C.34)

where the  $\beta$ s are given by:

$$\beta_{s,c} = \lambda \pi_s, \quad \beta_{s,x} = \kappa_{1,s} A_{1,s} \sqrt{1 - \rho^2} \varphi_x, \qquad \beta_{s,s} = \lambda, \quad \beta_{s,\omega_c} = \kappa_{1,s} A_{2,s,c}, \qquad \beta_{s,\omega_s} = \kappa_{1,s} A_{2,s,s}.$$

The risk premium for the software claim is

$$\mathbb{E}_{t}\left(r_{s,t+1} - r_{f,t}\right) + \frac{1}{2}\operatorname{Var}_{t}\left(r_{s,t+1}\right) = -\operatorname{Cov}_{t}\left(m_{t+1}^{\$}, r_{s,t+1}\right)$$

$$= \beta_{s,\omega_{c}}\lambda_{\omega_{c}}\sigma_{\omega_{c}}^{2} + (\beta_{s,c}\lambda_{c} + \beta_{s,x}\lambda_{x})\sigma_{c,t}^{2}$$
(C.35)

Finally, adjusting for the Jensen's terms, we obtain an expression for the ex ante expected excess returns:

$$\mathbb{E}_{t} \left( r_{s,t+1} - r_{f,t} \right) = \left( \beta_{s,c} \lambda_{c} + \beta_{s,x} \lambda_{x} - \frac{1}{2} \beta_{s,c}^{2} - \frac{1}{2} \beta_{s,x}^{2} \right) \sigma_{c,t}^{2} + \left( \beta_{s,\omega_{c}} \lambda_{\omega_{c}} - \frac{1}{2} \beta_{s,\omega_{c}}^{2} \right) \sigma_{\omega_{c}}^{2} - \frac{1}{2} \beta_{s,s}^{2} \sigma_{s,t}^{2} - \frac{1}{2} \beta_{s,\omega_{s}}^{2} \sigma_{\omega_{s}}^{2}$$
(C.36)

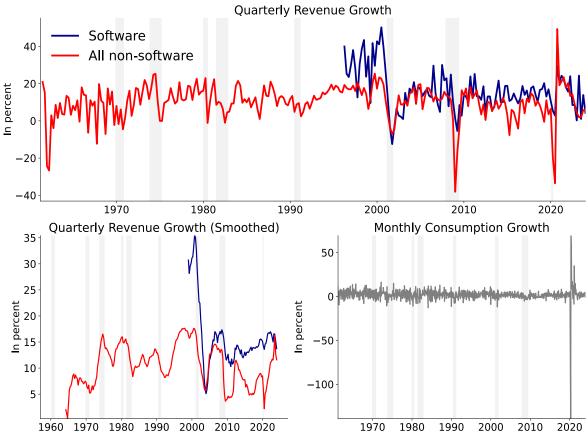
The ex post excess returns,  $r_{s,t+1} - r_{f,t}$ , are calculated by subtracting the risk-free rate in equation (C.28) from the return equation in (C.30). We define the  $\alpha$  as the difference between the sample average of the ex post excess returns and the ex ante expected excess returns, where the sample average is denoted by the expectations operator with a T subscript,  $\mathbb{E}_T$ :

$$\alpha = \mathbb{E}_T [r_{s,t+1} - r_{f,t}] - \mathbb{E}_T [\mathbb{E}_t (r_{s,t+1} - r_{f,t})]. \tag{C.37}$$

In the model section, we present results for  $\mathbb{E}_{T}\left[r_{s,t+1}-r_{f,t}\right]$ ,  $\mathbb{E}_{T}\left[\mathbb{E}_{t}\left(r_{s,t+1}-r_{f,t}\right)\right]$ , and  $\alpha$ .

## C.6 Supplementary figures and tables

Fig. C.1. Realized Growth Rates



Notes: The top panel displays the quarterly revenue growth series for software and non-software companies from 1959Q4 to 2023Q4. To highlight the low-frequency trends, the lower left panel presents these series smoothed using a 3-year rolling window. The lower right panel depicts the real per capita consumption growth series, which is available at a monthly frequency. To facilitate comparison, we annualize the quarterly series and present them in percent by multiplying by 400, while we annualize the monthly series and present them in percent by multiplying by 1200.

Table C.1. Initial Belief Distribution in 1996Q1

			Prior	
Parameter	Distribution	1%	50%	99%
	Consumption	growth process		
$\mu_c \times 100\%$	$\mathcal N$	0.16	0.18	0.19
ho	$\mathcal{N}^T$	0.87	0.94	1.00
$arphi_x$	$\mathcal N$	0.60	0.65	0.70
$\sigma \times 100\%$	$\mathcal{IG}$	0.19	0.28	0.43
$ ho_{h_c}$	$\mathcal{N}^T$	0.74	0.97	1.00
$ \rho_{h_c} $ $ \sigma_{h_c}^2 \times 100\% $	$\mathcal{IG}$	0.09	0.30	1.97
	Non-software	growth process		
$\mu_{ns} \times 100\%$	$\mathcal N$	0.71	0.75	0.78
$\phi_{ns}$	$\mathcal N$	10.48	11.00	11.53
$\pi_{ns}$	$\mathcal N$	0.15	0.20	0.25
$arphi_{ns}$	$\mathcal N$	1.16	1.50	1.84
$ ho_{h_{ns}}$	$\mathcal{N}^T$	0.73	0.97	1.00
$\sigma_{h_{ns}}^2 \times 100\%$	$\mathcal{IG}$	0.09	0.30	1.97
ivits	Software gr	owth process		
$\mu_s \times 100\%$	$\mathcal N$	0.72	0.75	0.78
$\phi_s$	$\mathcal N$	10.50	11.01	11.52
$\pi_s$	$\mathcal N$	0.15	0.20	0.25
$arphi_s$	$\mathcal N$	1.15	1.50	1.85
$ ho_{h_s}$	$\mathcal{N}^T$	0.73	0.97	1.00
$\sigma_{h_s}^2 \times 100\%$	$\mathcal{IG}$	0.09	0.30	1.98
0	Consumption m	neasurement err	or	
$\sigma_{\epsilon} \times 100\%$	$\mathcal{IG}$	0.12	0.17	0.27
$\sigma_{\epsilon}^q \times 100\%$	$\mathcal{IG}$	0.06	0.09	0.15

Notes: This table presents the initial belief distribution assumed 1996:Q1.  $\mathcal{N}$ ,  $\mathcal{N}^T$ , and  $\mathcal{IG}$  are normal, truncated (outside of the interval (-1,1)) normal, and inverse gamma distributions, respectively.

 $\phi_s$  and  $\phi_{ns}$  $\mu_s$  and  $\mu_{ns}$  $\pi_s$  and  $\pi_{ns}$  $arphi_s$  and  $arphi_{ns}$ 0.013 0.30 Software All non-software Software All non-software Software Software 0.012 All non-software 0.011 0.20 2.0 0.15 0.10 1,00 0.75 0.0030 0.0016 0.70 0.96 0.94 0.0022 0.92 0.0020 0.55 0.0016

Fig. C.2. Evolution of the Parameter Estimates

Notes: The figure shows the evolution of the posterior median estimates along with the 98% confidence intervals between 1996Q1 and 2023Q4.

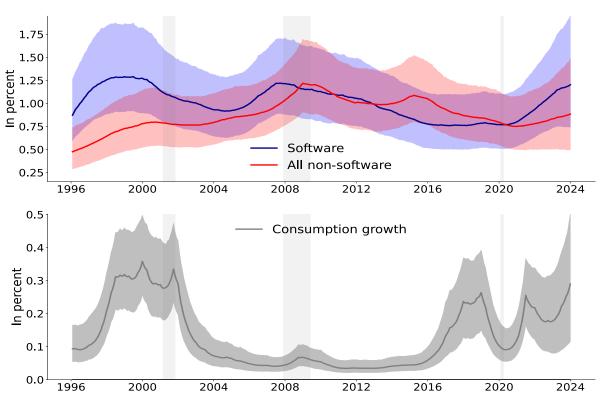


Fig. C.3. Stochastic Volatility Estimates

Notes: This figure shows the stochastic volatility estimates for software  $(\sigma_{s,t})$ , non-software  $(\sigma_{ns,t})$ , and consumption growth  $(\sigma_{c,t})$ , along with the 90% confidence intervals. NBER recession dates are indicated by gray shaded bars. The figure spans the period from January 1996 to December 2023.

Table C.2. One-Period P-Values of Updated Beliefs Given Priors

			5-year sı	napshots					
Parameter	1996	2000	2005	2015	2020	2023	min	mean	max
			Consum	otion gro	wth proc	ess			
$\mu_c$	1.00	0.54	0.64	0.39	0.50	0.46	0.20	0.54	1.00
ho	0.31	0.46	0.47	0.60	0.42	0.51	0.30	0.47	0.65
$\varphi_x$	0.36	0.27	0.43	0.89	0.25	0.28	0.02	0.48	0.99
$\sigma$	0.96	0.34	0.18	0.43	0.52	0.43	0.17	0.43	0.96
$ ho_{h_c}$	0.39	0.49	0.50	0.50	0.50	0.50	0.39	0.50	0.51
$ ho_{h_c} \\ \sigma_{h_c}^2$	0.12	0.37	0.41	0.36	0.35	0.36	0.12	0.36	0.49
700			Non-soft	ware gro	wth proc	ess			
$\mu_{ns}$	0.31	0.45	0.70	0.62	0.57	0.52	0.16	0.49	0.71
$\phi_{ns}$	0.74	0.51	0.64	0.69	0.73	0.87	0.12	0.59	0.91
$\pi_{ns}$	0.53	0.49	0.52	0.46	0.55	0.47	0.42	0.51	0.64
$\varphi_{ns}$	0.85	0.89	0.41	0.07	0.67	0.41	0.02	0.48	0.96
	0.39	0.50	0.50	0.50	0.50	0.50	0.39	0.50	0.53
$\begin{array}{c} \rho_{h_{ns}} \\ \sigma_{h_{ns}}^2 \end{array}$	0.43	0.32	0.29	0.28	0.34	0.41	0.01	0.38	1.00
· · · its			Softwa	re growt	h process	3			
$\mu_s$	0.35	0.46	0.24	0.57	0.55	0.47	0.16	0.47	0.86
$\phi_s$	0.48	0.57	0.19	0.50	0.65	0.41	0.10	0.57	0.99
$\pi_s$	0.50	0.57	0.52	0.51	0.47	0.57	0.45	0.53	0.64
$\varphi_s$	0.35	0.59	0.37	0.13	0.36	0.34	0.01	0.48	0.98
	0.39	0.51	0.51	0.50	0.50	0.51	0.39	0.50	0.53
$\begin{array}{c} \rho_{h_s} \\ \sigma_{h_s}^2 \end{array}$	0.43	0.32	0.29	0.28	0.34	0.40	0.01	0.38	1.00
8		$\mathbf{C}$	onsumpti	ion meas	urement	error			
$\sigma_\epsilon$	0.20	0.35	$0.50^{-}$	0.41	0.36	0.36	0.20	0.43	0.65
$\sigma^q_\epsilon$	0.00	0.62	0.91	0.40	0.51	0.41	0.00	0.45	0.93

Notes: This table presents the one-period p-values for each model parameter in  $\Theta$ , given the corresponding prior at time t. To compute these p-values, we simulated draws from the time t prior distribution of each parameter in  $\Theta$  and calculated the percentage of these draws that exceed the posterior median at time t+1. Columns 1 through 6 provide 5-year snapshots of these one-period p-values. The last three columns report the minimum, mean, and maximum values of these p-values over the entire sample period.

#### Alternative initial beliefs C.7

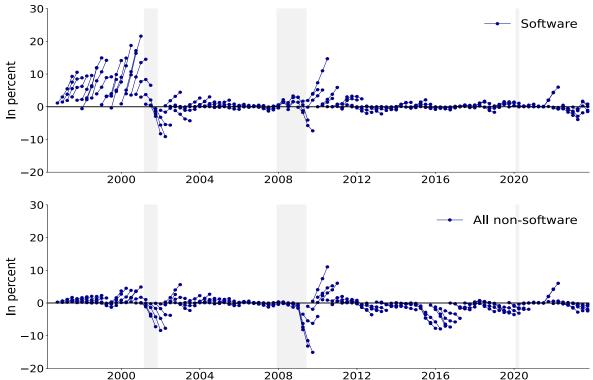
This section presents results for three alternative assumptions about agents' initial beliefs in our model.

Section C.7.1 examines agents with more dispersed initial beliefs about  $\Theta$ . We center the 1996 median beliefs about software around non-software beliefs, but allow a wider distribution of initial beliefs, though not wide enough to encompass the 2023 posterior median values. Section C.7.2 extends this approach, centering beliefs similarly but allowing an even wider distribution that does encompass the 2023 posterior median values. Finally, Section C.7.3 directly sets the initial beliefs in 1996 equal to the posterior median estimates in 2023, effectively endowing agents with perfect foresight about the end-of-sample parameters.

Fig. C.4. Biases in Model-Implied Forecasts: Loose Initial Beliefs

#### C.7.1Loose initial beliefs

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Notes: This figure shows the average model-implied forecast bias for every quarter in our sample for software companies, and all non-software companies. Each line in the figure represents the model-implied average forecast error across simulations for the current quarter and the subsequent three quarters. NBER recession dates are indicated by gray shaded bars.

Table C.3. Initial Belief Distribution in 1996Q1: Loose Initial Beliefs

			Prior	
Parameter	Distribution	1%	50%	99%
	Consumption	growth process		
$\mu_c \times 100\%$	$\mathcal N$	0.16	0.18	0.19
ho	$\mathcal{N}^T$	0.87	0.94	1.00
$arphi_x$	$\mathcal N$	0.60	0.65	0.70
$\sigma \times 100\%$	$\mathcal{IG}$	0.19	0.28	0.43
$ ho_{h_c}$	$\mathcal{N}^T$	0.74	0.97	1.00
$\sigma_{h_c}^2 \times 100\%$	$\mathcal{IG}$	0.09	0.30	1.97
	Non-software	growth process		
$\mu_{ns} \times 100\%$	$\mathcal N$	0.69	0.75	0.81
$\phi_{ns}$	$\mathcal N$	10.14	11.00	11.88
$\pi_{ns}$	$\mathcal N$	0.15	0.20	0.25
$arphi_{ns}$	$\mathcal N$	1.16	1.50	1.84
	$\mathcal{N}^T$	0.73	0.97	1.00
$\begin{array}{l} \rho_{h_{ns}} \\ \sigma_{h_{ns}}^2 \times 100\% \end{array}$	$\mathcal{IG}$	0.09	0.30	1.97
$n_s$	Software gr	owth process		
$\mu_s \times 100\%$	$\mathcal N$	0.69	0.75	0.81
$\phi_s$	$\mathcal N$	10.16	11.01	11.86
$\pi_s$	$\mathcal N$	0.15	0.20	0.25
$arphi_s$	$\mathcal N$	1.15	1.50	1.85
$ ho_{h_s}$	$\mathcal{N}^T$	0.73	0.97	1.00
$\sigma_{h_s}^2 \times 100\%$	$\mathcal{IG}$	0.09	0.30	1.98
108	Consumption m	easurement err	or	
$\sigma_{\epsilon} \times 100\%$	$\mathcal{IG}$	0.12	0.17	0.27
$\sigma_{\epsilon}^{q} \times 100\%$	$\mathcal{IG}$	0.06	0.09	0.15

Notes: This table presents the initial belief distribution assumed 1996:Q1.  $\mathcal{N}$ ,  $\mathcal{N}^T$ , and  $\mathcal{IG}$  are normal, truncated (outside of the interval (-1,1)) normal, and inverse gamma distributions, respectively.

Table C.4. Forecast Anomalies: Loose Initial Beliefs

		Soft	ware			Non-so	oftware	
	Foreca	st horiz	on in qu	ıarters	Forec	ast horiz	on in qua	arters
	1	2	3	4	1	2	3	4
A. Bias								
Model	0.46	1.05	1.63	2.19	-0.17	-0.40	-0.63	-0.89
	[1.78]	[1.75]	[1.72]	[1.67]	[-1.64]	[-1.64]	[-1.58]	[-1.53]
Data consensus	2.21	1.78	2.21	2.94	1.54	0.03	-1.41	-2.25
	[6.88]	[2.69]	[2.16]	[2.06]	[7.15]	[0.08]	[-2.36]	[-2.98]
Data individual	2.70	2.52	2.79	3.18	1.32	0.35	-0.01	0.11
	[13.69]	[5.99]	[4.34]	[3.98]	[7.42]	[0.83]	[-0.02]	[0.15]
B. Autocorrelati	<u>on</u>							
Model	0.31	0.60	0.42	0.37	0.43	0.27	0.07	-0.09
	[2.03]	[5.44]	[2.15]	[1.54]	[6.35]	[2.07]	[0.32]	[-0.52]
Data consensus	0.39	0.21	0.08	0.04	0.09	0.08	0.07	0.08
	[3.09]	[4.10]	[3.10]	[1.36]	[6.58]	[5.56]	[4.60]	[4.76]
Data individual	0.32	0.23	0.17	0.12	0.26	0.21	0.18	0.13
	[5.79]	[6.90]	[5.46]	[2.92]	[15.44]	[11.40]	[7.01]	[4.90]
C. Mincer-Zarno	$\overline{\text{witz}}$							
Model	1.13	1.11	1.05	0.98	1.06	1.00	0.93	0.82
	[0.61]	[0.44]	[0.20]	[-0.08]	[1.03]	[0.03]	[-0.74]	[-1.60]
Data consensus	0.98	0.92	0.91	0.88	0.86	0.85	0.83	0.81
	[-0.86]	[-2.37]	[-2.68]	[-1.73]	[-16.14]	[-14.69]	[-13.36]	[-8.66]
Data individual	0.97	0.92	0.95	1.01	0.83	0.82	0.82	0.78
	[-2.98]	[-3.77]	[-1.99]	[0.17]	[-16.52]	[-16.24]	[-15.66]	[-11.79]
D. Coibion-Goro	dnichen							
Model	-0.08	0.00	0.07		0.16	0.31	0.47	
	[-0.96]	[0.03]	[0.68]		[1.92]	[2.80]	[4.75]	
Data consensus	0.13	0.24	0.28		0.07	0.13	0.15	
	[8.37]	[7.65]	[6.22]		[6.07]	[5.23]	[6.04]	
Data individual	0.13	0.18	0.20		0.08	0.15	0.18	
	[6.62]	[4.38]	[4.09]		[5.95]	[4.00]	[4.58]	

Notes: This table presents four different tests of forecast rationality using model-implied forecasts, analyst consensus forecasts, and forecasts by individual analysts. The model-implied forecasts are derived using posterior median estimates. The t-statistics, presented in brackets, are relative to the following hypotheses: Bias = 0, Autocorrelation = 0, Mincer-Zarnowitz = 1, and Coibion-Gorodnichenko = 0. For the model-implied moments, Newey-West standard errors are used with the lag length selected as  $L = \left\lceil 1.3 \times T^{1/2} \right\rceil$ . For the data moments, standard errors are clustered by both firm and date. The forecast horizons are in quarters, and the forecast errors and forecast revisions used in the tests are expressed in percent. The sample spans from 1996Q1 to 2023Q3.

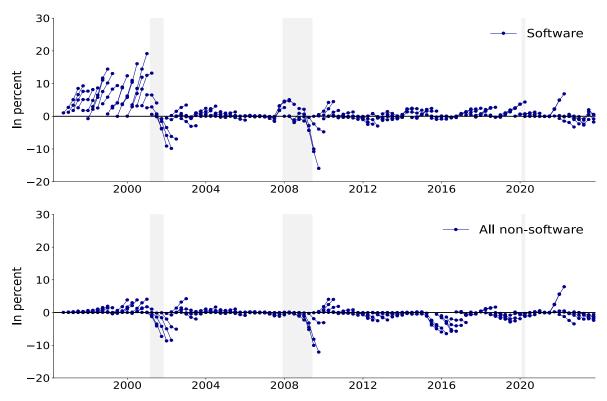
Table C.5. Performance Evaluation and Alphas: Loose Initial Beliefs

		Software	;	N	Non-software				
	Da	ata		Da	Data				
Name	EW	VW	Model	EW	VW	Model			
$E_T\left(r_{i,t+1}\right)$	18.54	15.67	7.95	10.93	9.95	4.50			
$E_T \left( r_{i,t+1} - r_{f,t} \right)$	16.44	13.57	6.06	8.83	7.86	2.61			
$E_T\left(\mathbb{E}_t\left(r_{i,t+1}-r_{f,t}\right)\right)$	10.73	9.31	4.07	9.27	8.44	4.02			
$\alpha$	5.71	4.27	1.99	-0.44	-0.58	-1.41			

Notes: This table reports asset pricing moments from the data and as implied by the model for both software and non-software companies. We report average ex post returns,  $E_T\left(r_{i,t+1}\right)$ , average ex post excess returns,  $E_T\left(r_{i,t+1}-r_{f,t}\right)$ , average ex ante excess returns,  $E_T\left(\mathbb{E}_t\left(r_{i,t+1}-r_{f,t}\right)\right)$ , and alphas,  $\alpha$ , where  $E_T$  denotes the sample average. For the data moments, we report these values using both equally-weighted (EW) and value-weighted portfolios (VW). To compute the average ex ante excess returns and alphas, we employ the Fama-French three-factor model. For the model-implied moments, we use the posterior median estimates and fix the preference parameters to  $\gamma=10$ ,  $\beta=0.999$ , and  $\psi=1.5$ . In both the model and the data, the frequency is monthly, and we report annualized values.

### C.7.2 Very Loose initial beliefs

Fig. C.5. Biases in Model-implied Forecasts: Very Loose Initial Beliefs



*Notes*: This figure shows the average model-implied forecast bias for every quarter in our sample for software companies, and all non-software companies. Each line in the figure represents the model-implied average forecast error across simulations for the current quarter and the subsequent three quarters. NBER recession dates are indicated by gray shaded bars.

Table C.6. Initial Belief Distribution in 1996Q1: Very Loose Initial Beliefs

			Prior	
Parameter	Distribution	1%	50%	99%
	Consumption	growth process	3	
$\mu_c \times 100\%$	$\mathcal N$	0.16	0.18	0.19
ho	$\mathcal{N}^T$	0.87	0.94	1.00
$arphi_x$	$\mathcal N$	0.60	0.65	0.70
$\sigma \times 100\%$	$\mathcal{IG}$	0.19	0.28	0.43
$ ho_{h_c}$	$\mathcal{N}^T$	0.74	0.97	1.00
$\sigma_{h_c}^2 \times 100\%$	$\mathcal{IG}$	0.09	0.30	1.97
	Non-software	growth process	3	
$\mu_{ns} \times 100\%$	$\mathcal N$	0.58	0.75	0.93
$\phi_{ns}$	$\mathcal N$	5.84	11.01	16.26
$\pi_{ns}$	$\mathcal N$	0.04	0.20	0.36
$arphi_{ns}$	$\mathcal N$	0.37	1.49	2.64
$ ho_{h_{ns}}$	$\mathcal{N}^T$	0.73	0.97	1.00
$\sigma_{h_{ns}}^2 \times 100\%$	$\mathcal{IG}$	0.09	0.30	1.97
113	Software gro	owth process		
$\mu_s \times 100\%$	$\mathcal N$	0.58	0.75	0.92
$\phi_s$	$\mathcal N$	5.96	11.05	16.18
$\pi_s$	$\mathcal N$	0.04	0.20	0.35
$arphi_s$	$\mathcal N$	0.34	1.51	2.65
$ ho_{h_s}$	$\mathcal{N}^T$	0.73	0.97	1.00
$\sigma_{h_s}^2 \times 100\%$	$\mathcal{IG}$	0.09	0.30	1.98
	Consumption m	easurement err	or	
$\sigma_{\epsilon} \times 100\%$	$\mathcal{IG}$	0.12	0.17	0.27
$\sigma_{\epsilon}^q \times 100\%$	$\mathcal{IG}$	0.06	0.09	0.15

Notes: This table presents the initial belief distribution assumed 1996:Q1.  $\mathcal{N}$ ,  $\mathcal{N}^T$ , and  $\mathcal{IG}$  are normal, truncated (outside of the interval (-1,1)) normal, and inverse gamma distributions, respectively.

Table C.7. Forecast Anomalies: Very Loose Initial Beliefs

		Soft	ware			Non-so	oftware	
	Foreca	st horiz	on in qu	ıarters	Forec	ast horiz	on in qua	arters
	1	2	3	4	1	2	3	4
A. Bias								
Model	0.40	0.88	1.32	1.72	-0.14	-0.34	-0.57	-0.83
	[1.80]	[1.71]	[1.57]	[1.43]	[-1.94]	[-2.15]	[-2.16]	[-2.02]
Data consensus	2.21	1.78	2.21	2.94	1.54	0.03	-1.41	-2.25
	[6.88]	[2.69]	[2.16]	[2.06]	[7.15]	[0.08]	[-2.36]	[-2.98]
Data individual	2.70	2.52	2.79	3.18	1.32	0.35	-0.01	0.11
	[13.69]	[5.99]	[4.34]	[3.98]	[7.42]	[0.83]	[-0.02]	[0.15]
B. Autocorrelati	<u>on</u>							
Model	0.29	0.44	0.37	0.28	0.47	0.28	0.06	-0.10
	[2.43]	[2.66]	[2.04]	[1.20]	[4.39]	[2.45]	[0.42]	[-0.90]
Data consensus	0.39	0.21	0.08	0.04	0.09	0.08	0.07	0.08
	[3.09]	[4.10]	[3.10]	[1.36]	[6.58]	[5.56]	[4.60]	[4.76]
Data individual	0.32	0.23	0.17	0.12	0.26	0.21	0.18	0.13
	[5.79]	[6.90]	[5.46]	[2.92]	[15.44]	[11.40]	[7.01]	[4.90]
C. Mincer-Zarno	$\overline{\text{witz}}$							
Model	1.22	1.26	1.23	1.18	1.04	1.04	1.01	0.94
	[1.97]	[1.67]	[1.32]	[0.91]	[1.30]	[0.94]	[0.14]	[-0.67]
Data consensus	0.98	0.92	0.91	0.88	0.86	0.85	0.83	0.81
	[-0.86]	[-2.37]	[-2.68]	[-1.73]	[-16.14]	[-14.69]	[-13.36]	[-8.66]
Data individual	0.97	0.92	0.95	1.01	0.83	0.82	0.82	0.78
	[-2.98]	[-3.77]	[-1.99]	[0.17]	[-16.52]	[-16.24]	[-15.66]	[-11.79]
D. Coibion-Goro	dnichen	<u>ko</u>						
Model	-0.13	0.00	0.15		0.02	0.12	0.27	
	[-1.42]	[0.06]	[2.03]		[0.72]	[2.40]	[3.66]	
Data consensus	0.13	0.24	0.28		0.07	0.13	0.15	
	[8.37]	[7.65]	[6.22]		[6.07]	[5.23]	[6.04]	
Data individual	0.13	0.18	0.20		0.08	0.15	0.18	
	[6.62]	[4.38]	[4.09]		[5.95]	[4.00]	[4.58]	

Notes: This table presents four different tests of forecast rationality using model-implied forecasts, analyst consensus forecasts, and forecasts by individual analysts. The model-implied forecasts are derived using posterior median estimates. The t-statistics, presented in brackets, are relative to the following hypotheses: Bias = 0, Autocorrelation = 0, Mincer-Zarnowitz = 1, and Coibion-Gorodnichenko = 0. For the model-implied moments, Newey-West standard errors are used with the lag length selected as  $L = \left\lceil 1.3 \times T^{1/2} \right\rceil$ . For the data moments, standard errors are clustered by both firm and date. The forecast horizons are in quarters, and the forecast errors and forecast revisions used in the tests are expressed in percent. The sample spans from 1996Q1 to 2023Q3.

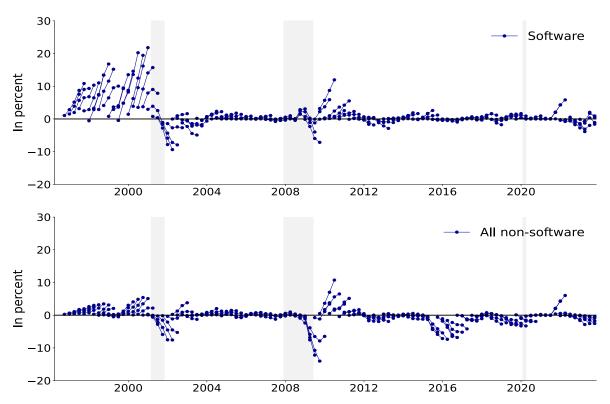
Table C.8. Performance Evaluation and Alphas: Very Loose Initial Beliefs

		Software		Non-software				
	Da	ata		Dε				
Name	EW	VW	Model	EW	VW	Model		
$E_T\left(r_{i,t+1}\right)$	18.54	15.67	5.17	10.93	9.95	2.45		
$E_T \left( r_{i,t+1} - r_{f,t} \right)$	16.44	13.57	3.22	8.83	7.86	0.50		
$E_T\left(\mathbb{E}_t\left(r_{i,t+1}-r_{f,t}\right)\right)$	10.73	9.31	3.63	9.27	8.44	3.75		
$\alpha$	5.71	4.27	-0.41	-0.44	-0.58	-3.25		

Notes: This table reports asset pricing moments from the data and as implied by the model for both software and non-software companies. We report average ex post returns,  $E_T\left(r_{i,t+1}\right)$ , average ex post excess returns,  $E_T\left(r_{i,t+1}-r_{f,t}\right)$ , average ex ante excess returns,  $E_T\left(\mathbb{E}_t\left(r_{i,t+1}-r_{f,t}\right)\right)$ , and alphas,  $\alpha$ , where  $E_T$  denotes the sample average. For the data moments, we report these values using both equally-weighted (EW) and value-weighted portfolios (VW). To compute the average ex ante excess returns and alphas, we employ the Fama-French three-factor model. For the model-implied moments, we use the posterior median estimates and fix the preference parameters to  $\gamma=10$ ,  $\beta=0.999$ , and  $\psi=1.5$ . In both the model and the data, the frequency is monthly, and we report annualized values.

### C.7.3 Look-ahead initial beliefs

Fig. C.6. Biases in Model-implied Forecasts: Look-Ahead Initial Beliefs



*Notes*: This figure shows the average model-implied forecast bias for every quarter in our sample for software companies, and all non-software companies. Each line in the figure represents the model-implied average forecast error across simulations for the current quarter and the subsequent three quarters. NBER recession dates are indicated by gray shaded bars.

Table C.9. Initial Belief Distribution in 1996Q1: Look-Ahead Initial Beliefs

		Prior			
Parameter	Distribution	1%	50%	99%	
	Consumption g	rowth process			
$\mu_c \times 100\%$	$\mathcal N$	0.08	0.09	0.10	
ho	$\mathcal{N}^T$	0.87	0.94	1.00	
$arphi_x$	$\mathcal N$	0.65	0.71	0.76	
$\sigma \times 100\%$	$\mathcal{IG}$	0.13	0.19	0.30	
$ ho_{h_c}$	$\mathcal{N}^T$	0.76	0.99	1.00	
$\sigma_{h_a}^2 \times 100\%$	$\mathcal{IG}$	0.38	1.26	8.35	
	Non-software g	rowth process			
$\mu_{ns} \times 100\%$	$\mathcal N$	0.76	0.80	0.84	
$\phi_{ns}$	$\mathcal N$	6.09	6.39	6.69	
$\pi_{ns}$	$\mathcal N$	0.11	0.14	0.17	
$\varphi_{ns}$	$\mathcal N$	1.62	2.09	2.57	
$ ho_{h_{ns}}$	$\mathcal{N}^T$	0.76	1.00	1.00	
$\sigma_{h_{ns}}^2 \times 100\%$	$\mathcal{IG}$	0.08	0.26	1.74	
rens	Software grov	wth process			
$\mu_s \times 100\%$	$\mathcal N$	0.85	0.89	0.93	
$\phi_s$	$\mathcal N$	6.53	6.84	7.16	
$\pi_s$	$\mathcal N$	0.07	0.09	0.11	
$arphi_s$	$\mathcal N$	1.71	2.23	2.74	
$ ho_{h_s}$	$\mathcal{N}^T$	0.76	1.00	1.00	
$\frac{\rho_{h_s}}{\sigma_{h_s}^2} \times 100\%$	$\mathcal{IG}$	0.08	0.26	1.75	
	Consumption me	asurement erro	or		
$\sigma_{\epsilon} \times 100\%$	$\mathcal{IG}$	0.09	0.13	0.20	
$\sigma_{\epsilon}^q \times 100\%$	$\mathcal{IG}$	0.07	0.10	0.17	

Notes: This table presents the initial belief distribution assumed 1996:Q1.  $\mathcal{N}$ ,  $\mathcal{N}^T$ , and  $\mathcal{IG}$  are normal, truncated (outside of the interval (-1,1)) normal, and inverse gamma distributions, respectively.

Table C.10. Forecast Anomalies: Look-Ahead Initial Beliefs

	Software				Non-software			
	Forecast horizon in quarters			Forecast horizon in quarters				
	1	2	3	4	1	2	3	4
A. Bias								
Model	0.42	0.99	1.59	2.19	-0.13	-0.29	-0.42	-0.56
	[1.57]	[1.56]	[1.55]	[1.54]	[-1.28]	[-1.18]	[-1.05]	[-0.96]
Data consensus	2.21	1.78	2.21	2.94	1.54	0.03	-1.41	-2.25
	[6.88]	[2.69]	[2.16]	[2.06]	[7.15]	[0.08]	[-2.36]	[-2.98]
Data individual	2.70	2.52	2.79	3.18	1.32	0.35	-0.01	0.11
	[13.69]	[5.99]	[4.34]	[3.98]	[7.42]	[0.83]	[-0.02]	[0.15]
B. Autocorrelati	<u>on</u>							
Model	0.41	0.59	0.50	0.41	0.37	0.27	0.10	-0.08
	[3.81]	[4.27]	[2.84]	[1.76]	[4.14]	[1.79]	[0.51]	[-0.45]
Data consensus	0.39	0.21	0.08	0.04	0.09	0.08	0.07	0.08
	[3.09]	[4.10]	[3.10]	[1.36]	[6.58]	[5.56]	[4.60]	[4.76]
Data individual	0.32	0.23	0.17	0.12	0.26	0.21	0.18	0.13
	[5.79]	[6.90]	[5.46]	[2.92]	[15.44]	[11.40]	[7.01]	[4.90]
C. Mincer-Zarno	$\overline{\text{witz}}$							
Model	1.24	1.24	1.17	1.08	1.05	1.02	0.95	0.85
	[1.17]	[0.86]	[0.59]	[0.29]	[0.94]	[0.23]	[-0.40]	[-1.12]
Data consensus	0.98	0.92	0.91	0.88	0.86	0.85	0.83	0.81
	[-0.86]	[-2.37]	[-2.68]	[-1.73]	[-16.14]	[-14.69]	[-13.36]	[-8.66]
Data individual	0.97	0.92	0.95	1.01	0.83	0.82	0.82	0.78
	[-2.98]		[-1.99]	[0.17]	[-16.52]	[-16.24]	[-15.66]	[-11.79]
D. Coibion-Goro	dnichen							
Model	-0.04	0.16	0.31		0.16	0.40	0.61	
	[-0.40]	[1.90]	[1.83]		[2.30]	[2.94]	[4.31]	
Data consensus	0.13	0.24	0.28		0.07	0.13	0.15	
	[8.37]	[7.65]	[6.22]		[6.07]	[5.23]	[6.04]	
Data individual	0.13	0.18	0.20		0.08	0.15	0.18	
	[6.62]	[4.38]	[4.09]		[5.95]	[4.00]	[4.58]	

Notes: This table presents four different tests of forecast rationality using model-implied forecasts, analyst consensus forecasts, and forecasts by individual analysts. The model-implied forecasts are derived using posterior median estimates. The t-statistics, presented in brackets, are relative to the following hypotheses: Bias = 0, Autocorrelation = 0, Mincer-Zarnowitz = 1, and Coibion-Gorodnichenko = 0. For the model-implied moments, Newey-West standard errors are used with the lag length selected as  $L = \left\lceil 1.3 \times T^{1/2} \right\rceil$ . For the data moments, standard errors are clustered by both firm and date. The forecast horizons are in quarters, and the forecast errors and forecast revisions used in the tests are expressed in percent. The sample spans from 1996Q1 to 2023Q3.

Table C.11. Performance Evaluation and Alphas: Look-Ahead Initial Beliefs

	Software			Non-software		
	Data			Data		
Name	EW	VW	Model	EW	VW	Model
$E_T\left(r_{i,t+1}\right)$	18.54	15.67	9.08	10.93	9.95	5.63
$E_T \left( r_{i,t+1} - r_{f,t} \right)$	16.44	13.57	7.33	8.83	7.86	3.87
$E_T\left(\mathbb{E}_t\left(r_{i,t+1}-r_{f,t}\right)\right)$	10.73	9.31	5.34	9.27	8.44	5.09
$\alpha$	5.71	4.27	1.98	-0.44	-0.58	-1.22

Notes: This table reports asset pricing moments from the data and as implied by the model for both software and non-software companies. We report average ex post returns,  $E_T\left(r_{i,t+1}\right)$ , average ex post excess returns,  $E_T\left(r_{i,t+1}-r_{f,t}\right)$ , average ex ante excess returns,  $E_T\left(\mathbb{E}_t\left(r_{i,t+1}-r_{f,t}\right)\right)$ , and alphas,  $\alpha$ , where  $E_T$  denotes the sample average. For the data moments, we report these values using both equally-weighted (EW) and value-weighted portfolios (VW). To compute the average ex ante excess returns and alphas, we employ the Fama-French three-factor model. For the model-implied moments, we use the posterior median estimates and fix the preference parameters to  $\gamma=10$ ,  $\beta=0.999$ , and  $\psi=1.5$ . In both the model and the data, the frequency is monthly, and we report annualized values.