

Some benchmarks with comp.g_secd

Ian D. Gow

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In this note, I use a simple query to benchmark performance of various approaches to accessing data in `comp.g_secd`. Many international researchers will know that `comp.g_secd` holds daily security-level data for non-US firms covered by Compustat Global. It is the global version of the North America daily security file, `comp.secd`, and, I guess, the closest analogue of `crsp.dsf` for finance and accounting researchers studying non-US firms.

I use this data set to do some benchmarking. I find that a query using `comp.g_secd` that takes 6 minutes using SAS on the WRDS servers, takes about 1 minute using the WRDS PostgreSQL server and about 0.2 seconds using a local Parquet file. The Parquet file occupies less than 4 GB on my hard drive, which compares with about 145 GB for the SAS file on the WRDS server. While creating the Parquet file takes 45 minutes, this may be a reasonable trade-off for a researcher who is analysing `comp.g_secd` frequently and does not need the very latest iteration of `comp.g_secd` for research purposes.

💡 Tip

In writing this note, I used the R packages listed below.¹ I also used Python for portions of the code. This note was written using [Quarto](#) and compiled with [RStudio](#), an integrated development environment (IDE) for working with R and Python. The source code for this note is available [here](#) and the latest version of this PDF is [here](#).

```
library(DBI)
library(tidyverse)
library(farr)
```

1 A little about WRDS data

In the beginning was the ... SAS data. Well, not really. Surely the databases such as CRSP and Compustat that have powered research in accounting and finance since the [beginning of time](#) predate SAS and

1. Execute `install.packages(c("tidyverse", "DBI", "duckdb", "dbplyr", "farr", "RPostgres"))` within R to install all the packages you need to run the code in this note.

WRDS. But since long before I entered a business PhD program, WRDS has been the preeminent provider of data to academic researchers and SAS was long the form in which WRDS provided data.

In 2011, I created a predecessor of my `wrds2pg` Python package to create a PostgreSQL database containing WRDS data.² The `wrds2pg` package has developed over time, but almost nothing has changed since 2023.³

By early 2017, WRDS offered its own PostgreSQL database. Early on the data in the WRDS PostgreSQL database was not complete and it seemed to have been created from the SAS data files, but generally was of lower quality than what I had in my database (e.g., `wrds2pg` did a better job with inference of data types and handled non-Latin characters better). But today it is unclear whether the SAS data or the PostgreSQL data are the “canonical” version of the data; they can probably both be considered canonical data sources.

Working in R with data in databases such as PostgreSQL has been greatly facilitated by [the `dbplyr` Tidyverse package](#). I don’t recall exactly when I started using `dbplyr`, but I have email exchanges with Hadley Wickham about backend functionality for PostgreSQL as far back as 2015 and I can barely remember the days when I didn’t have it. I would say that `dbplyr` is what made the code approach used in Gow and Ding (2024) feasible, even if [some critical pieces](#) fell into place after work on the book began. Today, packages such as `Ibis` mean that a similar approach could be taken with Python.⁴

In late 2023, I added functionality to `wrds2pg` that allows SAS files to be turned into Parquet files. The Parquet file format is provided by Apache Arrow, “a software development platform for building high performance applications that process and transport large data sets.”⁵ The Parquet format offers much of the versatility of CSV files, while also allowing for a rich system of data types and random access to data. As seen in [Chapter 23](#) of Gow and Ding (2024), Parquet files can be combined with DuckDB to provide a lightweight, high-performance alternative to PostgreSQL.

Also in late 2023, I created [the `db2pq` Python library](#) to create Parquet files directly from a PostgreSQL database. Around the same time, I updated the [online version](#) of Gow and Ding (2024) to include a Parquet variant of the code and I used this approach when teaching courses based on the book in 2024. While the `db2pq` package has a mere 29 commits on [GitHub] at the time of writing, it has seen more recent development than the `wrds2pg` package.⁶

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2. My original code was in Perl, but by 2015 I had Python code to do the same job, and by 2019 there was an installable Python package, created with the help of [Jingyu Zhang](#). Early on, I considered SQLite and MySQL as well as PostgreSQL, but I decided on PostgreSQL because of its rich type system, powerful SQL, and support for server programming (though I ended up not using the last one much). Though I had zero expertise, it seems that I somehow made the right choice. I was also an early adopter of RStudio in 2010 or 2011.
 3. The only recent change was I recently exposed the (previously internal) `sas_to_pandas()` function that I used in [my recent note](#) on SAS and pandas.
 4. Trying to do Gow and Ding (2024) using pandas and SQL would be painful and slow.
 5. See the Apache Arrow website at <https://arrow.apache.org/overview/>.
 6. A lot of early work involved using poorly documented libraries to keep the memory impact to a minimum and to facilitate the `wrds_update_pq()` conditional-update functionality.

So in this note, I will compare three alternative approaches to `comp.g_secd`: SAS data (using SAS), PostgreSQL data (using R), and Parquet data (using R).⁷

With that short detour into the history of WRDS data and so on out of the way, I now return to the topic of `comp.g_secd` and I focus initially on the “original” SAS data.

2 Exploration of `comp.g_secd` (SAS data)

While researchers looking for security returns for US-listed firms data can use CRSP’s `crsp.dsfc`, CRSP does not cover non-US firms. Fortunately, `comp.g_secd` provides high-quality data and (importantly) merging with Compustat fundamental data (i.e., `comp.g_funda`) is facilitated by the shared identifiers across these tables (i.e., `gvkey` and `iid`).

The fields on `comp.g_secd` include its security identifiers. The firm identifier is `gvkey` and the issue identifier—crucial for firms with multiple share classes or listings—is `iid`. As I will confirm below, the natural **primary key** for `comp.g_secd` is (`gvkey`, `iid`, `datadate`).

There are two files on the WRDS server for `comp.g_secd`: `g_secd.sas7bdat` (144.8 GB) and `g_secd.sas7bndx` (23.1 GB).⁸ The `g_secd.sas7bdat` file is the SAS data file that will be familiar to users of SAS. But even SAS users may be unfamiliar with `g_secd.sas7bndx`, which is the index file. Index files have much the same role for SAS data files as indexes do for tables in SQL databases, such as the WRDS PostgreSQL database that I will discuss in a moment.

If a SAS user copies `g_secd.sas7bdat` onto her computer *without* the index, then query performance is likely to be degraded in many cases. We can inspect the indexes that WRDS has created using the PROC CONTENTS procedure from SAS. If you have my package `wrds2pg` installed, then `proc_contents()` provides a convenient way to access this procedure in Python:⁹

```
from wrds2pg import proc_contents
proc_contents("g_secd", "comp")
```

The output from the Python code above is shown in Listings 1, 2, and 3 at the end of this document. The information on the indexes is provided at the bottom of Listing 3, where you can see that there are five indexes. Four indexes relate to single fields: `isin`, `sedol`, `exchg`, and `fic`. Each of these indexes improves performance of queries that focus on particular values of the associated variable. The fifth index is on `gvkey` and `datadate` and allows one to quickly zero in on particular combinations of those variables, as would be the case if merging with a subset of `comp.g_funda` for which `gvkey` and `datadate` is a primary key.¹⁰

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7. Note that the “using R” part is relatively unimportant. For example, it would be easy to do everything with essentially identical performance using Python.
 8. If you look at Listing 1, you may notice “135GB”; this is incorrect and should be “135 GiB” (a GiB is a “binary” unit in which $1 \text{ GiB} = 2^{30} = 1,073,741,824$ bytes).
 9. Note that the following Python code use the environment variable `WRDS_ID`. Call `proc_contents("g_secd", "comp", wrds_id="your_wrds_id")` if you don’t have this set.
 10. For example, analogues of `funda_mod` as described in Chapter 6 of Gow and Ding (2024).

2.1 The benchmark query

Now that we understand a little about `comp.g_secd` and its SAS manifestation, I will introduce my benchmark query. The idea of the benchmark is that it is somewhat representative of the kinds of things a researcher might want to do with `comp.g_secd` without being overly complicated. Additionally, the benchmark should require actually looking at a significant part of the data (in this case *all* records) and, to keep it interesting, it should not be able to use a short cut of simply looking at an index.¹¹

The SAS version of my benchmark query simply counts the number of rows associated with each value of `curcdd`, which Listing 2 tells us represents “ISO Currency Code - Daily”:

```
proc sql;
  CREATE TABLE curcdd_counts AS
    SELECT curcdd, count(*) AS n
    FROM comp.g_secd
    GROUP BY curcdd
    ORDER BY n DESC;
quit;

proc print data=curcdd_counts;
run;
```

I put this SAS code into a file `g_secd.sas` in my home directory on the WRDS server and ran `qsas g_secd.sas`. Inspecting `g_secd.log` a few minutes later, I see The SAS System used: real time 6:08.66. So SAS needs more than 5 minutes to run this query. And here is a sample of the output in `g_secd.lst`:

The SAS System 1
Wednesday, February 18, 2026 01:55:00 PM

Obs	curcdd	n
1	EUR	48130467
2	JPY	31841749
3	CNY	25687260
4	INR	20676444
5	GBP	20636852
6	KRW	15657569
7	HKD	14717583
8	AUD	13812258

11. Whether queries can use such shortcuts obviously depends on the specifics of the available indexes (in this case, there is no index to use for `curcdd`), but also on whether the backend system will use them for the query.

3 Using the WRDS PostgreSQL server

Now, let's do the same query using the WRDS PostgreSQL server. I have my WRDS ID in the WRDS_ID environment variable and I have my password stored in `~/.pgpass`, so I can use PostgreSQL-related environment variables to point R to the WRDS server.

```
Sys.setenv(PGHOST = "wrds-pgdata.wharton.upenn.edu",
            PGPORT = 9737L,
            PGUSER = Sys.getenv("WRDS_ID"),
            PGDATABASE = "wrds")
```

Now, two lines of code suffice to set up a connection to `comp.g_secd` on the WRDS PostgreSQL server.

```
db <- dbConnect(RPostgres::Postgres())
g_secd <- tbl(db, Id(schema = "comp", table = "g_secd"))
```

With `dbplyr`, we can write the query as follows.¹²

```
g_secd |>
  count(curcdd) |>
  arrange(desc(n)) |>
  collect() |>
  system_time()
```

```
user    system elapsed
0.014   0.017  150.921
```

```
# A tibble: 115 x 2
  curcdd      n
  <chr>    <int64>
1 EUR        48037544
2 JPY        31823971
3 CNY        25635258
4 INR        20653714
5 GBP        20619033
6 KRW        15641761
7 HKD        14697439
8 AUD        13800095
9 TWD        11646012
```

12. Note that `system_time()` comes from the `farr` package.

```
10 THB      8980840
# i 105 more rows
```

We see two things here. First, the output is slightly different from that above, suggesting that the SAS data are slightly newer (higher numbers) than the PostgreSQL data. I will return to this point below. Second, the PostgreSQL server delivers the query about six times faster than SAS does.

4 Using Parquet data

Now, I do it again using Parquet data. The first step is to update (or get the data) using the following two lines of Python code. Again, this code relies on WRDS_ID and DATA_DIR environment variables. I specify archive=True to keep a copy of any existing g_secd.parquet file I have.

```
from db2pq import wrds_update_pq
wrds_update_pq("g_secd", "comp", archive=True)
```

```
comp.g_secd already up to date.
False
```

When I did this update earlier today, it took a bit over 45 minutes on my computer. But, as can be seen above, wrds_update_pq() will not fetch new data if the data are up to date.

However, WRDS updates Compustat data every day. As this may not be an update you'd want to be running every day, the daily updates might be "more bug than feature" for many researchers.

Now, two lines of code suffice to set up a connection to a DuckDB database pointing to the comp.g_secd Parquet file on my hard drive.

```
db <- dbConnect(duckdb::duckdb())
g_secd <- load_parquet(db, table = "g_secd", schema = "comp")
```

Now, we can run exactly the same query as we did for the WRDS PostgreSQL server.

```
g_secd |>
  count(curcdd) |>
  arrange(desc(n)) |>
  collect() |>
  system_time()
```

```
user  system elapsed
1.501  0.092  0.188
```

```
# A tibble: 115 x 2
  curcdd      n
  <chr>    <dbl>
1 EUR      48130467
2 JPY      31841749
3 CNY      25687260
4 INR      20676444
5 GBP      20636852
6 KRW      15657569
7 HKD      14717583
8 AUD      13812258
9 TWD      11656464
10 THB     8987656
# i 105 more rows
```

Wow! So *once we have the data in Parquet form*, the query is blazingly fast. Something taking over 6 minutes on the SAS “supercomputers” takes about 0.2 seconds on my consumer-grade Mac mini.

Note that the results match the output from the PostgreSQL server exactly, because we updated the data before running the query.

I now make a little Python function to get information about the size of the Parquet file that has been created.

```
from pathlib import Path
import os

def file_size(path) -> str:
    n_bytes = path.stat().st_size
    for unit in ["B", "KB", "MB", "GB", "TB", "PB"]:
        if n_bytes < 1024:
            return f"{n_bytes:.1f} {unit}"
        n_bytes /= 1024
    return f"{n_bytes:.1f} EB"
```

Now, I run this function on the Parquet file created by `wrds_update_pq()`.

```
data_dir = Path(os.environ["DATA_DIR"]).expanduser()
path = data_dir / "comp" / "g_secd.parquet"
file_size(path)
```

'3.8 GB'

So the 57.71 GB PostgreSQL table is reduced to under 4 GB as a Parquet file.¹³ This is much more manageable!

Returning to the mismatch between the output from the SAS query and the PostgreSQL query, we can inspect the “last modified” data for the Parquet file, which are taken from the table comments on the PostgreSQL server.

```
from pathlib import Path
from db2pq import pq_last_modified
import os
```

Running this function on the main file tells us that the PostgreSQL table was updated yesterday, explaining why we see the difference from the WRDS SAS output above:

```
pq_last_modified("g_secd", "comp")
```

'Merged Global Security Daily File (Updated 2026-02-17)'

We can run the function with archive=True to see what we have in the archive:

```
pq_last_modified("g_secd", "comp", archive=True)
```

	file_name	...	storage
0	g_secd_20250907T161453Z	...	local
1	g_secd_20260120T070000Z	...	local
2	g_secd_20260216T070000Z	...	local

[3 rows x 6 columns]

The one archived file I have has an update string taken from the SAS file existing on the WRDS server when that update occurred.¹⁴

Gow, I.D., Ding, T., 2024. Empirical research in accounting: Tools and methods. Chapman & Hall/CRC, London, UK. <https://doi.org/10.1201/9781003456230>

13. Note that the PostgreSQL server, like SAS, also has one or more indexes, which occupy an additional 15.75 GB.

14. A recent update to db2pq means that the “last updated” string comes from the comments appended to the PostgreSQL table.

Listing 1 Output from PROC CONTENTS with comp.g_secd (Part 1)

The SAS System

The CONTENTS Procedure

Data Set Name	COMP.G_SECD	Observations	302719472
Member Type	DATA	Variables	54
Engine	V9	Indexes	5
Created	02/24/2026 10:08:46	Observation Length	496
Last Modified	02/24/2026 10:16:33	Deleted Observations	0
Protection		Compressed	NO
Data Set Type		Sorted	YES
Label	Merged Global Security Daily File		
Data Representation	SOLARIS_X86_64, LINUX_X86_64, ALPHA_TRU64, LINUX_IA64		
Encoding	utf-8 Unicode (UTF-8)		

Engine/Host Dependent Information

Data Set Page Size	65536
Number of Data Set Pages	2293331
First Data Page	1
Max Obs per Page	132
Obs in First Data Page	111
Index File Page Size	8192
Number of Index File Pages	2864639
Number of Data Set Repairs	0
Filename	/wrds/comp/sasdata/d_global/g_secd.sas7bdat
Release Created	9.0401M8
Host Created	Linux
Inode Number	2465334812
Access Permission	rw-r-----
Owner Name	wrdsadmn
File Size	140GB
File Size (bytes)	150295805952

Listing 2 Output from PROC CONTENTS with comp.g_secd (Part 2)

Alphabetic List of Variables and Attributes					
#	Variable	Type	Len	Format	Informat Label
46	ISIN	Char	21	\$12.	International Security Identification Number
48	SEDOL	Char	21	\$7.	SEDOL
6	ajexdi	Num	8	F19.8	20.8
					Adjustment Factor (Issue)-Cumulative by Ex-Date
34	anncdate	Num	8	YYMMDDN8.	Dividend Declaration Date
16	cheqv	Num	8	F17.4	18.4
17	cheqvgross	Num	8	F17.4	18.4
18	cheqvnet	Num	8	F17.4	18.4
					Cash Equivalent Distributions, Gross
					Cash Equivalent Distributions, Net of Tax
35	cheqvpayda	Num	8	YYMMDDN8.	Cash Equivalent Distributions per Share Payment Date
	te				
19	cheqvtm	Char	3	\$2.	\$3.
					Cash Equivalent Distributions Tax Code
4	comm	Char	87	\$87.	\$87.
7	cshoc	Num	8	F19.	19.
8	cshtrd	Num	8	F29.8	30.8
5	curcdd	Char	4	\$3.	\$4.
15	curcddv	Char	4	\$3.	\$4.
3	datadate	Num	8	YYMMDDN8.	Data Date - Daily Prices
20	div	Num	8	F17.4	18.4
					Dividends per Share - Ex Date - Daily (Issue)
21	divd	Num	8	F17.4	18.4
22	divdgross	Num	8	F17.4	18.4
23	divdnet	Num	8	F17.4	18.4
36	divdpaydat	Num	8	YYMMDDN8.	Cash Dividends - Daily Payment Date
	te				
24	divdtm	Char	3	\$2.	\$3.
25	divgross	Num	8	F17.4	18.4
					Cash Dividend including Special, Gross
26	divnet	Num	8	F17.4	18.4
					Cash Dividend including Special, Net of Tax
27	divrc	Num	8	F17.4	18.4
28	divrcgross	Num	8	F17.4	18.4
29	divrcnet	Num	8	F17.4	18.4
37	divrcpayda	Num	8	YYMMDDN8.	Return of Capital - Daily Payment Date
	te				

Listing 3 Output from PROC CONTENTS with comp.g_secd (Part 3)

30	divsp	Num	8 F17.4	18.4	Special Cash Dividends - Daily
31	divspgross	Num	8 F17.4	18.4	Special Cash Dividends, Gross
32	divspnet	Num	8 F17.4	18.4	Special Cash Dividends, Net of Tax
38	divsppayda	Num	8 YYMMDDN8. te		Special Cash Dividends - Daily Payment Date
33	divsptm	Char	3 \$2.	\$3.	Special Cash Dividend Tax Code
44	epf	Char	2 \$1.	\$2.	Earnings Participation Flag
45	exchg	Num	8 F6.	6.	Stock Exchange Code
50	fic	Char	4 \$3.	\$4.	Current ISO Country Code - Incorporation
51	gind	Char	7 \$6.	\$7.	GIC Industries
52	gsubind	Char	9 \$8.	\$9.	GIC Sub-Industries
1	gvkey	Char	7 \$6.	\$7.	Global Company Key - Daily Prices
2	iid	Char	4 \$3.	\$4.	Issue ID - Daily Price
53	loc	Char	4 \$3.	\$4.	Current ISO Country Code - Headquarters
54	monthend	Num	8		End of Month Indicator
39	paydate	Num	8 YYMMDDN8.		Dividend Payment Date
9	prccd	Num	8 F29.8	30.8	Price - Close - Daily
10	prchd	Num	8 F29.8	30.8	Price - High - Daily
11	prcld	Num	8 F29.8	30.8	Price - Low - Daily
12	prcod	Num	8 F29.8	30.8	Price - Open - Daily
13	prcstd	Num	8 F6.	6.	Price Status Code - Daily
14	qunit	Num	8 F17.4	18.4	Price Quotation Unit
40	recorddate	Num	8 YYMMDDN8.		Dividend Record Date
47	secstat	Char	2 \$1.	\$2.	Security Status Marker
41	split	Num	8 F19.8	20.8	Stock Split Rate
42	splitf	Char	9 \$8.	\$9.	Stock Split Footnote
49	tpci	Char	9 \$8.	\$9.	Issue Type Code
43	trfd	Num	8		Daily Total Return Factor

Alphabetic List of Indexes and Attributes

#	Index		# of Unique Values	Variables
1	ISIN		92479	
2	SEDOL		122182	
3	exchg		156	
4	fic		131	
5	gvkey_datadate	245676188		gvkey datadate

Sort Information

11

Sortedby gvkey iid datadate
 Validated YES
 Character Set ASCII
