Getting SEC EDGAR XBRL data

Ian D. Gow

2 December 2024

In a recent note, I used XBRL data to identify potentially missing Form AP filings. In writing that note, I used two data sources: SEC EDGAR for the XBRL data and the PCAOB website for the Form AP data. However, I provided no real information on how to get the XBRL data from SEC EDGAR. This note aims to provide this missing information.[1]

This note was written using Quarto and compiled with RStudio, an integrated development environment (IDE) for working with R. The source code for this note is available here and the latest version of this PDF is here.

This note uses the following R packages:[2]

```r
library(tidyverse)
library(DBI)
library(farr)
library(httr2)
library(rvest)
library(arrow)
```

Getting *Financial Statement and Notes* files

There are two XBRL bulk data sets made available on SEC EDGAR: the *Financial Statements* and *Financial Statement and Notes* data sets, with the latter being roughly ten times as large as the former. For the task considered in the note discussed above, we needed the *Financial Statement and Notes* data set, so I focus on that data set here.

[1] Guidance on downloading the Form AP data is provided in an earlier note I wrote.

[2] To install these packages, run `install.packages(c(tidyverse, "DBI", "farr", "httr2", "rvest", "arrow")` in the console of RStudio.

Structure of processed data

The *Financial Statement and Notes* data library comprises seven tables:

- `tag` contains all standard taxonomy tags (not just those appearing in submissions to date) and all custom taxonomy tags defined in the submissions. The standard tags are derived from taxonomies in the SEC's standard taxonomies file as of the date of submission.
- `dim` contains all of the combinations of XBRL axis and member used to tag any submission.
- `num` contains numeric data, one row per data point in the financial statements.
- `txt` contains non-numeric data, one row per data point in the financial statements.
- `ren` summarizes for each filing the data provided by filers about each presentation group as defined in EDGAR filer manual.
- `pre` contains one row for each line of the financial statements tagged by the filer.
- `cal` contains one row for each calculation relationship ("arc"). Note that XBRL allows a parent element to have more than one distinct set of arcs for a given parent element, thus the rationale for distinct fields for the group and the arc.[3]

Structure of unprocessed data

If you visit the *Financial Statement and Notes* site, you will see something like the table partially seen in Figure 1. This table provides links to many ZIP files. The last year or so of data are found in monthly data files and earlier periods are found in quarterly data files. Each data file is found using a link provided in the table.

I start with the `2024_10` file, the link to which points to a file named `2024_10_notes.zip`. We can download that file and extract its contents, which are depicted in Figure 2. It seems that each of the data tables discussed above is found in an eponymous `.tsv` file.

I start with `sub.tsv` and I repeat the download steps for the `.zip` file programmatically. To programmatically download data from SEC EDGAR, you will need to set `HTTPUserAgent` to *your* email address by running code like the following in R.

```
options(HTTPUserAgent = "your_name@email_provider.com")
```

While we are on the topic of setting variables that are user-specific, we will later store data in a subdirectory of a directory that is identified by the environment variable `DATA_DIR`. I set `DATA_DIR` to a folder named `pq_data` inside my Dropbox location. You should run the following code but with a destination that is convenient for you.

[3]Run `source("https://raw.githubusercontent.com/iangow/notes/refs/heads/main/get_dera_notes.R")` to get these data.

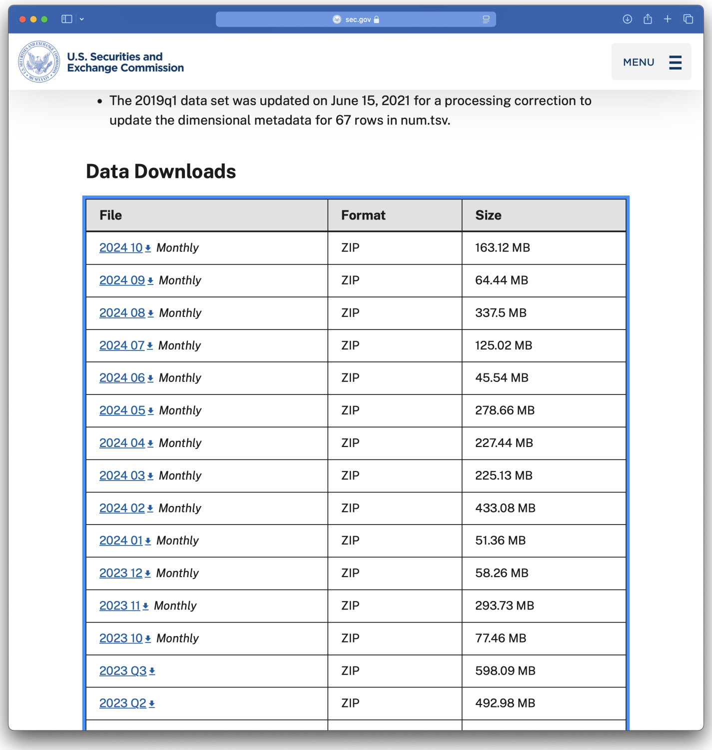

Figure 1: Financial Statement and Notes website

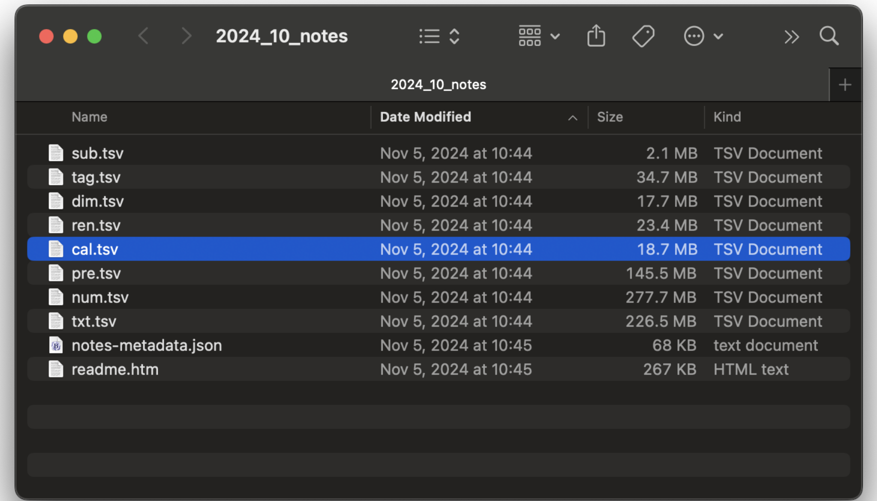

Figure 2: Contents of `2024_10_notes.zip`

```r
Sys.setenv(DATA_DIR = "~/Dropbox/pq_data")
```

Having set `HTTPUserAgent`, I begin by downloading the file for October 2024.

```r
file <- "2024_10_notes.zip"
url <- str_c("https://www.sec.gov/files/dera/data/",
             "financial-statement-notes-data-sets/", file)
t <- "../data/2024_10_notes.zip"
download.file(url, t)
```

We can start by simply applying `read_tsv()` to this file.[4]

```r
sub <- read_tsv(unz(t, "sub.tsv"))
```

```
Warning: One or more parsing issues, call `problems()` on your data frame for details,
e.g.:
  dat <- vroom(...)
  problems(dat)

Rows: 7117 Columns: 40
-- Column specification --------------------------------------------------------
Delimiter: "\t"
chr  (26): adsh, name, sic, countryba, stprba, cityba, zipba, bas1, bas2, ba...
dbl  (12): cik, changed, wksi, period, fy, filed, prevrpt, detail, nciks, pu...
lgl   (1): floataxis
dttm  (1): accepted

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Alas, we see problems. What's the cause? Let's follow the prompt and use `problems()` to investigate.

```r
problems(sub)
```

```
# A tibble: 1 x 5
    row   col expected           actual       file
  <int> <int> <chr>              <chr>        <chr>
1  1620    39 1/0/T/F/TRUE/FALSE ClassOfStock ""
```

[4] Using `unz(t, "sub.tsv")` allows us to unzip just that one file in a way that does not leave detritus in our file system.

It seems that `read_tsv()` guessed that column 39 is a logical variable (i.e., `TRUE` or `FALSE`), which is inconsistent with the value `"ClassOfStock"` observed in row 1620. Maybe setting `guess_max` to a higher value will help.

```
sub <- read_tsv(unz(t, "sub.tsv"), guess_max = 10000)
```

```
Rows: 7117 Columns: 40
-- Column specification --------------------------------------------------------
Delimiter: "\t"
chr  (27): adsh, name, sic, countryba, stprba, cityba, zipba, bas1, bas2, ba...
dbl  (12): cik, changed, wksi, period, fy, filed, prevrpt, detail, nciks, pu...
dttm  (1): accepted

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

OK, no problems now. What are the types of each column? Here I apply a small function `first_class()` to sub to find out.[5]

```
first_class <- function(x) {
  class(x)[[1]]
}

unlist(map(sub, first_class))
```

```
       adsh         cik        name         sic   countryba      stprba
"character"   "numeric" "character" "character" "character" "character"
     cityba       zipba        bas1        bas2        baph   countryma
"character" "character" "character" "character" "character" "character"
     stprma      cityma       zipma        mas1        mas2  countryinc
"character" "character" "character" "character" "character" "character"
    stprinc         ein      former     changed         afs        wksi
"character" "character" "character"   "numeric" "character"   "numeric"
        fye        form      period          fy          fp       filed
"character" "character"   "numeric"   "numeric" "character"   "numeric"
   accepted     prevrpt      detail    instance       nciks       aciks
  "POSIXct"   "numeric"   "numeric" "character"   "numeric" "character"
pubfloatusd   floatdate   floataxis   floatmems
  "numeric"   "numeric" "character"   "numeric"
```

[5]I use `first_class()` to get just the first class for each column as one column has two classes associated with it. You can see this by running `unlist(map, sub, class))` and comparing the output with that from the code I use below.

```r
table(unlist(map(sub, first_class)))
```

```
character   numeric   POSIXct
       27        12         1
```

While most columns are either `character` or `numeric`, the `accepted` column is read as a date-time (`POSIXct`).

The `read_tsv()` function has a `col_types` argument that allows us to "use a compact string representation where each character represents one column" as follows:

- c = character
- i = integer
- n = number
- d = double
- l = logical
- f = factor
- D = date
- T = date time
- t = time
- ? = guess
- _ or - = skip

The following `get_coltypes_str()` function creates a string that we can use to specify column types when calling `read_tsv()`.[6]

```r
get_coltypes_str <- function(df) {
  type_to_str <- function(col) {
    case_when(col == "character" ~ "c",
              col == "logical" ~ "l",
              col == "numeric" ~ "d",
              col == "POSIXct" ~ "T",
              .default = "c")
  }

  res <-
    tibble(type = unlist(map(sub, first_class))) |>
    mutate(col_type = type_to_str(type))

  paste(res$col_type, collapse = "")
```

[6]This function only handles a subset of the types that might be identified by `read_tsv()`, but it suffices for current purposes.

```
}

get_coltypes_str(sub)
```

```
[1] "cdcccccccccccccccccccdcdccddcdTddcdcddcd"
```

Even though `read_tsv()` is able to guess most types, it is generally best to look at the data. In this case, we can see that four columns are actually dates coded as numbers of the form `yyyymmdd`.

```
sub |>
  select(changed, filed, period, floatdate) |>
  arrange(floatdate)
```

```
# A tibble: 7,117 x 4
    changed    filed   period floatdate
      <dbl>    <dbl>    <dbl>     <dbl>
 1 20050502 20241004 20221231  20220630
 2 20080808 20241002 20240531  20221130
 3 20220308 20241028 20231231  20221231
 4       NA 20241009 20240731  20230131
 5 20101025 20241029 20230731  20230131
 6       NA 20241029 20240731  20230131
 7 20120910 20241029 20240731  20230131
 8 20101025 20241031 20230731  20230131
 9 20030416 20241029 20230930  20230331
10 20001117 20241002 20231231  20230630
# i 7,107 more rows
```

In the following code, I use `ymd()` to convert these four variables into dates. I also read `accepted` initially as a character variable and use `ymd_hms()` from the `lubridate` package to convert it to a date-time.[7]

```
sub <-
  read_tsv(unz(t, "sub.tsv"),
           col_types = "cdcccccccccccccccccccdcdccddcdcddcdcddcd") |>
   mutate(across(c(changed, filed, period, floatdate), ymd),
          across(accepted, ymd_hms))
```

[7] I do not recall why I chose this option, but it may have been that the automatic type detection and conversion did not work with all files and setting it explicitly works best.

Finally I create a DuckDB instance and copy the data frame `sub` to DuckDB, giving it the name `sub_notes`.

```
db <- dbConnect(duckdb::duckdb())
sub |>
  copy_to(db, df = _, name = "sub_notes", overwrite = TRUE)
```

Finally, I create a parquet file by exporting the data from the DuckDB table I just created. I then disconnect from the database, as I no longer need it.

```
period <- str_replace(basename(t), "^(.*)_notes.*$", "\\1")
pq_dir <- file.path(Sys.getenv("DATA_DIR"), "dera_notes")
pq_file <- file.path(pq_dir, str_c("sub_notes_", period, ".parquet"))
dbExecute(db, str_c("COPY sub_notes TO '", pq_file, "'"))
```

```
[1] 7117
```

```
dbDisconnect(db)
```

I then do similar work for the remaining tables (`dim`, `num`, `txt`, `ren`, `pre`, and `cal`). I then put all of this inside a function `get_notes_data(file)` that downloads a `.zip` file and creates parquet files for each table. I can load this function by running the following code:

```
source(str_c("https://raw.githubusercontent.com/iangow/",
             "notes/refs/heads/main/get_dera_functions.R"))
```

This code also loads the function `get_zip_files_df()` that can be used to get the list of `.zip` files shown on SEC website.

```
zip_files <- get_zip_files_df()
zip_files
```

```
# A tibble: 77 x 2
   file              last_modified
   <chr>             <chr>
 1 2026_01_notes.zip Wed, 04 Feb 2026 17:27:33 GMT
 2 2025_12_notes.zip Wed, 14 Jan 2026 20:59:24 GMT
 3 2025_11_notes.zip Thu, 15 Jan 2026 14:09:07 GMT
 4 2025_10_notes.zip Mon, 01 Dec 2025 14:48:45 GMT
 5 2025_09_notes.zip Tue, 18 Nov 2025 21:32:32 GMT
```

```
 6 2025_08_notes.zip Wed, 03 Sep 2025 16:10:15 GMT
 7 2025_07_notes.zip Tue, 05 Aug 2025 16:57:51 GMT
 8 2025_06_notes.zip Thu, 03 Jul 2025 18:46:28 GMT
 9 2025_05_notes.zip Tue, 03 Jun 2025 11:09:16 GMT
10 2025_04_notes.zip Wed, 07 May 2025 17:47:37 GMT
# i 67 more rows
```

Next, I can apply the function `get_notes_data()` to each file in `zip_files` using `map()`:

```r
map(zip_files$file, get_notes_data)
```

Doing this takes me a bit under 38 minutes.[8] The resulting files take up about 39 GB of space, likely representing about 10 times that in terms of raw data due to compression.

Doing incremental updates

While 38 minutes is a reasonable amount of time to download hundreds of gigabytes of data, it is not something that we would want to repeat on a regular basis. The astute reader will note that the `last_modified` field of `zip_files` contains information on the date on which the applicable file was modified. It seems we could use this information to limit ourselves to files that have been added or modified since we last updated the data.

In the past I have use three different approaches to this kind of problem:

1. Storing `last_modified` data in the metadata of parquet files containing the data.
2. Modifying the file properties of the data file to match the `last_modified` data.
3. Saving a table containing `last_modified` data that can be compared with the current data to identify files that need to be downloaded.

Of these three approaches, the first is probably the most robust because the `last_modified` information is part of the parquet file itself. I use this first approach in `wrds_update_pq()` in two Python packages, `wrds2pg` and `db2pq`. The second approach also collocates the information with the file, but is perhaps a little less robust. I use this approach in `wrds_update_csv()` in `wrds2pg` because the output files are CSV files where there is no place to store metadata.

Here I will use the third approach just because it is simpler. However it is a little less robust. For example, if the download process is interrupted or the data files are moved around, the value of a directory-level file with `last_modified` might be limited.

I start by loading a file called `last_modified.parquet` in the parquet data directory if one exists. The first time you run the code, there will be no such file and I create an empty data frame `last_modified` in that case.

[8] Obviously the time taken will depend on the speed of your internet connection and your "distance" from the SEC EDGAR server.

```r
pq_dir <- file.path(Sys.getenv("DATA_DIR"), "dera_notes")
pq_path <- file.path(pq_dir, "last_modified.parquet")

if (file.exists(pq_path)) {
  last_modified <- arrow::read_parquet(pq_path)
} else {
  last_modified <- tibble(file = NA, last_modified = NA)
}
```

I then compare `zip_files` with `last_modified` to identify files on SEC EDGAR with a different modification date from that recorded in `last_modified`. These are the files that we will want to download and we store the list of such files in the data frame `to_update`.

```r
to_update <-
  zip_files |>
  left_join(last_modified,
            by = "file",
            suffix = c("_new", "_old")) |>
  filter(is.na(last_modified_old) |
           last_modified_new != last_modified_old)
```

Now I can apply `get_notes_data()` to the files in `to_update`.

```r
map(to_update$file, get_notes_data)
```

Having updated the files, we now save the data in `zip_files` as the new copy of `last_updated`. This new `last_updated.parquet` will be used the next time we update the data.

```r
save_parquet <- function(df, name) {
  file_path <- file.path(pq_dir, paste0(name, ".parquet"))
  arrow::write_parquet(df, sink = file_path)
}

zip_files |>
  save_parquet(name = "last_modified")
```

According to the SEC EDGAR website, "effective March 2024, monthly data sets will be consolidated into quarterly files after a year, so that only a year of monthly files will be available at a time." This will mean that monthly files will become obsolete after about a year and presumably need to be deleted to avoid duplicating data in quarterly files. A subsequent update to this note will discuss how we can identify and delete obsolete files.

Using *Financial Statement and Notes* data

Now that we have downloaded the data, we can access it quite easily using DuckDB and the `load_parquet()` function from the `farr` library.[9] Note that while the tables are split across several files, these are easily combined using wildcards in DuckDB. For example, `sub_notes_*` can be used to refer to all files that make up the submission data (`sub` table). As can be seen, working with parquet files using DuckDB is generally very fast.

```
db <- dbConnect(duckdb::duckdb())

sub <- load_parquet(db, "sub_notes_*", schema = "dera_notes")

sub |>
  mutate(year = year(filed)) |>
  count(year) |>
  arrange(desc(year)) |>
  collect() |>
  system_time()
```

```
   user  system elapsed
  0.040   0.014   0.027
```

```
# A tibble: 18 x 2
    year      n
   <dbl>  <dbl>
 1  2026   5428
 2  2025  99208
 3  2024 194501
 4  2023 104015
 5  2022  97814
 6  2021  82740
 7  2020  60923
 8  2019  35040
 9  2018  26396
10  2017  26557
11  2016  34431
12  2015  29906
13  2014  31219
14  2013  31798
15  2012  32755
```

[9] The `farr` package was originally created to supplement the book by me and Tony Ding, *Empirical Research in Accounting: Tools and Methods*.

16	2011	18337
17	2010	3914
18	2009	951